**Design and Analysis of Algorithms**

**Frequency Count Method**

Ex - 1 :- Algorithm sum(A , n)

Input : A – array of n elements

1 . s <- 0 ----------- 1 time

2 . for(i=0 ; i < n ; i++) -------- (i=0) -> 1 time , (i<n) -> n + 1 times and (i++) -> n times , But we will consider only (n+1)times

3 . s <- s + A[i] ---------- n times

4 .end for

5 .return s ------ 1 time

Analyzation :-

**TIME COMPLEXITY**

-Each statement will take 1 unit of time .

Hence , total unit of time taken = 1 + (n+1) + n + 1 = (2n + 3) unit of time , OR

Time-function , f(n) = 2n + 3 , since the degree of the polynomial is 1

hence , ***time-complexity = O(n)***

**SPACE COMPLEXITY**

-Each variable will take 1 word of memory

Hence , A takes n words , and

n , s , i will take 1 word each

hence , total space , S(n) = n+3 , since its degree is also 1

***space-complexity = O(n)***

Ex – 2 : - Analyze the time and space complexity of an algorithm of sum of two n\*n matrices

Algorithm add(A,B,n)

Input : A , B – Two square matrices with n\*n dimensions

1 . for(i=0;i<n;i++) ------------ (n+1) times

2 . for(j=0;j<n;j++) ---------- n \* (n+1) times

3 . C[i,j] = A[i,j] + B[i,j] ------ n \* n times

4 . end for

5 . end for

**TIME COMPLEXITY**

Hence , Time function f(n) = 2n2 + 2n + 1 , since degree = 2(since the highest order-term is 2n2)

***Time-complexity = O(n2)***

**SPACE COMPLEXITY**

A , B , C - n\*n words each ; i , j , n – 1 word each

Hence , Space function S(n) = 3 n2+ 3 , degree = 2

***Space – complexity = O(n2)***

Ex – 3 :- Analyze the algorithm of multiplication of two square matrices of n\*n dimension .

Algorithm product(A,B,n)

1 . for(i=0;i<n;i++) --------- (n+1) times

2 . for(j=0;j<n;j++) -------(n+1)\*n times

3 . C[i,j] = 0 ; --------n \* n times

4 . for(k=0;k<n;k++) -------n\*n\*(n+1) times

5 . C[i,j] = C[i,j] + A[i,k]\*B[k,j] -----------n\*n\*n times

6 . end for

7 . end for

8 . end for

Time-function f(n) = 2 n3 + 3 n2 + 2n + 1 , degree = 3

***Time-complexity = O(n3)***

Space-function S(n) = 3 n2 + 4 , degree = 2

***Space – complexity = O(n2)***

Ex – 4 :-

1 . for(i=0;i<n;i++) ----------(n+1) times

2 . for(j=0;j<i;j++) -----------{n\*(n+1)/2 + 1} times

3 . stataement . ----------------n\*(n+1)/2 = **(n2 + n)/2**

4. end for

5 . end for

In the 4th statement ,

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| i | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | n |
| freq(j) | 0 times | 1 times | 2 times | 3 times | 4 times | 5 times | 6 times | 7 times | n times |

Hence , total time taken by j = 1 + 2 + 3 + 4 + 5 + 6…. + n = n\*(n+1)/2

hence , the 4th statement will run **[n\*(n+1)/2]+1 times**

***Time-complexity = O(n2)***

Ex – 5 :-

1 . p <- 0

2 . for(i=1 , p<=n , i++)

3 . p = p + i

4 . end for

Assume that p becomes greater than n i.e **p>n** after **k times** , hence , the statement will run k times , Hence , *Time-complexity = O(k)*

then after k times , p = 1 + 2 + 3 + ….+ k = k\*(k+1)/2 = **(k2  + k)/2**

* P > n
* K^2 > n
* K = (n1/2)

Hence ***, Time-complexity = O(n1/2)***

Ex – 6 :-

1 . for(i=1 , i<n , i=i\*2)

2 . statement

3 . end for

Suppose the loop runs **k** times to stop(i.e **i>n**) , hence , **i = 2k** and time-complexity = O(k)

At time k **, i > n => 2k > n => k = log(n2) ,** Hence ***Time-complexity = O(logn2)***

* *In Algorithm analysis we take* ***ceil value*** *of log , i.e for decimal values we take the next largest integer ex:– 3.2 = 4*

Ex- 7 :-

1 . for(i=n , i>=1 , I = i/2)

2 . statement

3 . end for

=> Assume after **k** times loop stops i.e **i<1** , and **i = n/2k-1** , then , *time-complexity = O(k)*

=> **i < 1** => **n/2k-1 = 1** => **n = 2k-1** **=> logn = (k-1)log2** => **k-1 = log n2** => **k = log n2** (discarded 1 from RHS)

Hence ***, Time-complexity = O(log n)***

Ex – 8:-

1 . p = 0

2 . for(i=1,i<n,i=i\*2) ------- (**log n2**) times

3 . p++ ---------( **log n2**) times , hence , **p = log n2**

4 . end for

5 . for(j=1,j<p,j=j\*2) ------ (log p) times or **(log (log n2))** times

6 . statement ------- (log p) times or **(log (log n2))** times

7 . end for

Hence time-function , **F(n) = 2 (log (log n2)) + 2 log n2**

***Time-complexity = O(log (*log n2*))***

Ex-9 :-

1 .for(i=0 ; i < n ; i++) ---------- n times

2 . for(j = 1 , j<n , j=j\*2) --------(n\* **log n2**) times

3 . statement ---------- (n\* **log n2**) times

4 . end for

5 . end for

**{We are discarding the constant parts of time functions in each step for our convenience as only highest order terms decide the time-complexity}**

Time function ***, f(n) = 2(n\** log n2*) + n*** , since the highest order term is n\*logn , hence ,

***Time-complexity = O(n\** log n2*)***

**General observed notions for time-complexities :-**

1 . for(i=0 , i<n , i++) ----***n times , O(n)*** *time taken by i=0 and i++ are constants(1) ,hence ignored*

2 . for(i=0 , i<n , i = i+2) ------***n/2 times , O(n)***

3 . for(i=n , i>1 , i--) --------- ***n times , O(n)***

4 . for(i=1 , I <n , i=i\*2) ------ ***log2n times , O(log2n)***

5 . for(i=n , i>1 , i=i/2) ----- ***log2n times , O(log2n)***

6 . for(i=1 , i<n , i=i\*3) ----- ***log3n times , O(log3n)***

7 . for(i=n , i>1 , i=i/3) ----- ***log3n times , O(log3n)***

***\* We can ignore the constant and lower order terms in the time function , since only degree of the function or highest order terms are responsible for time-complexity .***

**Analysis of If & while**

Ex-1 :

i = 0 ; 1 time

while(i<n) n+1 times

{

statement ; n times

i++ ; n times

}

Time-function T(n) = 3n + 2 , degree = 1 , highest order monomial 3n

**time-complexity : O(n)**

|  |  |
| --- | --- |
| iteration(times) | value of a |
| 1 | 2 |
| 2 | 22 |
| 3 | 23 |
| k | 2k |

Let after k iterations/times , loop/function stops and a = 2k and a >=b

**2k>=b ; 2k=b ; log2k=logb ; k = log2b** , assume , b=n

hence , ***Time-complexity : O(logn)***

Ex-2 :

a = 1 ; 1 time(ignored)

while(a<b)

{

statement ;

a = a\*2 ;

}

Ex - 3 :

|  |  |  |
| --- | --- | --- |
| Iteration/time | value of k | value of i |
| 1 | 2 | 2 |
| 2 | 2+2 | 3 |
| 3 | 2+2+3 | 4 |
| 4 | 2+2+3+4 | 5 |
| 5 | 2+2+3+4+5 | 6 |
| m | 1+2+3+4+5+….+m (roughly) = m\*(m+1)/2 | m+1  or **m (roughly)** |

Let assume after m times loop terminates , then value of k = m\*(m+1)/2 and k>=n

or , **k = m2 (roughly) ; m2 = n ; m = n1/2**

***Time-complexity : O(n1/2)***

***\*We can use the rough values in order to get time-complexities , like we did in last row***

1 time(ignored)

i = 1 ;

1 time(ignored)

k = 1 ;

while(k<n)

{

statement ;

k = k + i ;

i++ ;

}

Ex - 4 :

if m = 16 n =2 , Time complexity will be around O(m) which is maximumum time and can be termed as **worst case**

but , if m = n and if m=6 n=3 , loop will terminate in 1 time only with complexity O(1)

and can be termed as **best case**

**\*Hence , if conditional statement is present in the loop , then time complexities may vary as per the conditions and inputs and can result *best and worst case time-complexities***

while(m!=n)

{

if(m>n)

m=m-n;

else

n=n-m;

}

**Types of time-complexities or orders as per classes of corresponding time-functions**

Constant

**O(1)**

**O(logn)**

Linear

Logarithmic

**O(n)**

Quadratic

**O(n2)**

Cubic

**O(n3)**

Exponential

**O(2n) , O(nn)**

1<logn<n1/2<n<nlogn<n2<n3…..<2n<3n<nn  (Order of Functions)

**Aymptotic Notations**

**O** big-oh upper-bound

**Ω** big-omega Lower-bound

**ø** theta Average-bound

**O** big-oh

Definition :- The function f(n) = O(g(n)) , if there exist , positive constants c and no such that f(n) <= c\*g(n) for all n>=no .

e.g f(n) = 2n+3 => 2n+3 <= 10n , n>=1 this inequality satisfies , here g(n) = n , c = 10

hence , **f(n) = O(n)**

let , f(n) = 2n+3 and => 2n+3 <= 5n2 n>=1 , here , g(n) = n2

hence , **f(n) = O(n2)**

**- n** and **n2** and all the functions greater than these are the **upper bounds** and all the functions lower than n including it are the **lower bounds** and n only is the **average bound**

- Since all the functions above n are the upper bound than , f(n) = O(n) , f(n) = O(n2)…..f(n) = O(nn) , all are true **but only O(n) is meaningful** , as O(big-oh) represents the upper bound of the function , **but we consider only the most closest one i.e** f(n) = O(n) .

But , f(n) = O(logn) is false , since it is lower bound and lower bound is represented by big-omega(**Ω** big-omega)

**Ω** big-omega

Definition :- The function f(n) = **Ω(g(n)) ,** if there exist positive constants c and no such that , f(n) >= c\*g(n) for all n>=no .

e.g f(n) = 2n+3 => 2n+3 >= 1\*n , n>=1 , here g(n) = n , c =1 , hence , f(n) = Ω(n)

alse , => 2n+3 >= 1\*logn , hence , f(n) = Ω(logn)

hence , f(n) = Ω(n) , f(n) = Ω(logn) , f(n) = 1 , all are true(**but only Ω(n) is meaningful** ) as these are the lower bounds , **but we consider the most closest one only i.e** f(n) = Ω(n) .

**ø** theta

Definition :- The function f(n) = theta(g(n)) if there exist +ve constants c1 ,c2 and no  such that c1\*g(n)<=f(g(n)) <= c2\*g(n)

i.e f(n) = 2n+3 => 1\*n <= 2n+3 <=5\*n , for every n>=1 , here c1 = 1 , c2=5 g(n) = n

hence , average bound of f(n) is theta(n) or , f(n) = theta(n)

f(n) = theta(n2) or anything else won’t be true , **because theta gives average bound and it is single only**

Examples:-

1 . f(n) = 2n2 + 3n + 4 => 2n2 + 3n + 4 <= 2n2 + 3n2 + 42 => 2n2 + 3n + 4<= 9n2 for all n>=1

hence , f(n) = O(n2)

also , 2n2 + 3n + 4 >= 1\* n2 hence , f(n) = Ω(n2)

also , n2 <= 2n2 + 3n + 4 <= 9n2 hence , f(n) = theta(n2)

2 . f(n) = n2logn + n n2logn <= n2logn + n <= 10n2logn

hence , f(n) = O(n2logn) , f(n) = Ω(n2logn) and f(n) = theta(n2logn)

3 . f(n) = fact(n) = 1\*2\*3\*…\*n 1\*1\*1\*1..\*1 <= fact(n) <= n\*n\*n…\*n 1<= fact(n) <= nn

hence , f(n) = O(nn) and f(n) = Ω(1)

4 . f(n) = log fact(n) = log 1\*2\*3\*…\*n log 1\*1\*1\*..\*1 <= log fact(n) <= log n\*n\*n\*..\*n

1 <= log fact(n) <= log nn hence , f(n) = O(nlogn) and f(n) = Ω (1)

**Properties of Asymptotic Notations**

1 . General Property :- if f(n) is O(g(n)) then a\*f(n) is also O(g(n))

e.g : f(n) = 2n2 + 5 is O(n2) , then 7\*f(n) = 14n2 + 35 is also O(n2)

- General Property will be true for omega and theta also

2 . Reflexive Property :- if f(n) is given then f(n) = O(f(n))

3 . Transitive Property :- If f(n) is O(g(n)) and g(n) is O(h(n)) , then f(n) = O(h(n))

e.g : Suppose f(n) = n g(n) = n2 h(n) = n3

here , n = O(n2) and n2=O(n3) , hence n = O(n3)

- It is true for all the asymptotic notations

4 . Symmetric Property :- if f(n) is theta(g(n)) then g(n) is theta(f(n))

e.g : f(n) = n2 and g(n) = n2, then f(n) = theta(n2) and g(n) = theta(n2) or theta(f(n))

- this is true only for theta notation

5 . Transpose Symmetric :- if f(n) = O(g(n)) then g(n) is omega(f(n))

e.g : f(n) = n and g(n) = n2 then f(n) = O(n2) and g(n) = omega(n) or Omega(f(n))

6 . If f(n) = O(g(n)) also , f(n) = omega(g(n)) , then f(n) = Theta(g(n))

7 . If f(n) = O(g(n)) and d(n) = O(e(n)) then **f(n) + d(n) = O(max(g(n),e(n)))**

ex:- f(n) = n , O(n) and d(n) = n2 , O(n2) , then f(n) + d(n) = n2 + n , and hence O(n2)

8 . If f(n) = O(g(n)) and d(n) = O(e(n)) , then **f(n)\*d(n) = O(g(n)\*e(n))**

**Comparison of function**