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\theta notation, 0 \le C_1 g(n) \le f(n) \le C_2 g(n)

More on Asymptotic Notation
Proof: Let and g(n) be two asymptotic non-negative functions, then max (f(n), g(n)) = \Theta(f(n) + g(n))
       Let, h(n) = max(f(n), g(n)) \sim
 Then, h(n) = \begin{cases} f(n), & \text{if } f(n) > g(n) \\ g(n), & \text{if } f(n) < g(n) \end{cases}
Since f(n) and g(n) are asymptotically non-negative, there exists no p.t. f(n) > 0 and g(n) > 0, + n > n_0
 Thus, for n \ge n_0, f(n) + q(n) \ge f(n) \ge 0
and f(n) + q(n) \ge q(n) \ge 0
  Since for any particular n, h(n) is either f(n) or
  g(n), we have f(n)+g(n)>h(n)>0, which shows that h(n)=\max(f(n),g(n))\leq C_2\cdot(f(n)+g(n)), \forall n>n.
                                                            [c2=1 here]
 Similarly, since for any particular n, h(n) is
the larger of f(n) and g(n), we have \forall n \ge n_0,
                                             0 \leq f(n) \leq h(n)
 and o \leq q(n) \leq h(n)}
Adding these two inequalities,
                                               0 \leq f(n) + g(n) \leq 2 \cdot h(n)
                                          or, 0 < (f(n) + g(n))/2 < h(n)
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which shows that $h(n) = \max(f(n), g(n))$ $\forall n \ge n_0$ $\ge c_1(f(n) + g(n))$ $[c_1 = \frac{1}{2}here]$ (Proved) Proof: For two non-negative asymptotic functions, f(n) and g(n), $O(f(n)) + O(g(n)) = O(\max(f(n), g(n)))$ · Let, f(m) < g(m) / From the basic definition of Big-oh, we can write, $O(f(n)) + O(g(n)) \le C_1 f(n) + C_2 g(n)$, c, C_1 , C_2 $\leq c_1 q(n) + c_2 q(n)$ [As per our $\leq (c_1 + c_n) \cdot q(n)$] [As per our $\leq (c_1+c_2).g(r)$ assumption] $\leq c.q(n)$ [:: $c=c_1+c_2$] So, O(f(n)) + O(g(n)) = O(max(f(n), g(n)))Ex: For two non-negative asymptotic functions f(n) and g(n), O(f(n)) * O(g(n)) = O(f(n)*g(n))

. Prove that, n = o(an) for a>1 To lim f(n) = 0 $f(n) = n^k$, $g(n) = a^n$ (here) $\lim_{N\to\infty}\frac{n^{K}}{\alpha^{N}}=\frac{\infty}{\infty}$ So, applying L' Hospital's rule, $\lim_{n\to\infty} \frac{f(n)}{g(n)} = \lim_{n\to\infty} \frac{k \cdot n^{k-1}}{a^n \cdot \ln a} = \lim_{n\to\infty} \frac{k(k-1) \cdot n^{k-2}}{a^n \cdot \ln^2 a}$ So, $n^k = O(\alpha^n)$ (Proved) · Show that log n = O (m) but m = O (log n) First lim $f(n) = \lim_{n \to \infty} \frac{\log n}{\sqrt{n}} = \frac{\infty}{\infty} \left[f(n) = \log n \right]$ Applying L'Hospital's rule, $\lim_{n\to\infty}\frac{f(n)}{g(n)}=\lim_{n\to\infty}\frac{1/n}{\frac{1}{2}\cdot n^{-1/2}}=\lim_{n\to\infty}\frac{2}{\sqrt{n}}=0$ So, logn=0(m) (Proved) Second rose lim $f(n) = \lim_{n \to \infty} f(n) = \lim_{n \to \infty} f(n)$ $\lim_{n\to\infty} \frac{f'(n)}{g'(n)} = \lim_{n\to\infty} \frac{\frac{1}{2} \cdot n^{-1/2}}{\frac{1}{2}} = \lim_{n\to\infty} \frac{1}{2} = \infty$ $1 + \infty = \infty$ $1 + \infty$ $1 + \infty = \infty$ $1 + \infty$ 1

Proof of correctness for finding maximum of all elements in an array Algorithm Maximum(A) { // A is an array 1. max:= A[0]; 2. for i:= 1 to A. length-1 step 1 do 3. if A[i] > max then 4. max:=A[i];
5. return max; Case 1: A is having only one element Case 2: A is having more than one element The only element present in A, will be returned as max. > Loop invariant: It is a condition which must hold true during entire execution of the loop. For this algorithm, For any given value is max will contain maximum of elements whose index is smaller than i. Method of induction: For the first time at loop, i=1 and max will have the first element of the array, which is the greatest one till now. Now, we have to prove that loop invariant will hold at the end of the loop iteration.

for any given value i, the "if" inside "for" loop is executed. If value at position i, i. e. A[i]> then max will have new value, making max, maximum of all elements till now.

Otherwise, value of max will remain same.

So, either way, max will reflect the max" value from 0 to i, both inclusive.

So, by induction, when we traverse the entire length of the arrow, max will reflect maximum of arrowy A. (Proved)

Calculating time complexity of recursive algorithm: 1+2++n T(n) * Time required to compute f(n) int f (int n)

{
if (n==0) else return (n+f(n-1)); $T(n) = \begin{cases} t_1, & \text{when } n=0 \\ T(n-1)+t_2, & \text{when } n > 1 \end{cases}$ $\begin{cases} t_1, t_2 = constants. \end{cases}$ Recurrence relation. Solving recurrence relation: (1) Method of substitution 2) Recursion tree (3) Moster theorem $T(n) = T(n-1) + t_2$ = $\frac{1}{(n-2)+t_2+t_2}$ [As $\tau(n-1)=\tau(n-2)+t_2$] = T(n-2) + 2t2

$$= T(n-2)+t_2+t_2 \text{ [As T(n s)]}$$

$$= T(n-2)+2t_2$$

$$= T(n-3)+3t_2$$
After $(k-1)^{th}$ substitution, $T(n)=T(n-k)+Kt_2$
Putting $K=n$, we get, $T(n)=T(0)+nt_2$

$$[T(n)=t_1, when n=0] = t_1+nt_2$$

$$O(n)$$

· Find the time complexity of the following function. int f (int n) $T(n) = \begin{cases} t_1, & \text{when } n=1\\ T(n/2) + t_2, & \text{when } n \ge 2 \end{cases}$ {
if (n = = 1)
return 1; $T(r) = T(\gamma_2) + t_2$ return (f(n/2)+1); Putting $n = 2^k$ we have, $T(2^k) = T(2^{k-1}) + t_2$ $T(2^{K}) = T(2^{K-2}) + 2t_2$ [Applying method of substitution] $= T(2^{k-3}) + 3t_2$ After $(m-i)^{th}$ substitution, $T(2k) = T(2^{k-m}) + mt_2$ Putting K=m, = T(20)+Kt2 = T(1)+Kt2 T(2K) = +1+K+2 [:T(1)=+1] Now, $n=2^{k} \Rightarrow k=\log_{2}n$ $T(n) = t_1 + (\log_2 n) \cdot t_2$ O(logn)

Solvet the following recurrence relation by method of substitution.

$$T(n) = \begin{cases} T(n-1) + \log n, & \text{when } n > 1 \\ 0, & \text{when } n = 0 \end{cases}$$

$$T(n) = T(n-1) + \log n$$

= $T(n-2) + \log(n-1) + \log n$
= $T(n-3) + \log(n-2) + \log(n-1) + \log^{n} n$

$$= T(n-n) + log(n-n+1) + \cdots + log(n-2) + log(n-1)$$
[After (n-1)th substitution] + log n

$$= T(0) + \log n + \log (n-1) + \log (n-2) + \dots + \log 1$$

$$T(n) = C + \log \ln n$$

$$\frac{O(n \log n)}{D(n \log n)} = \frac{\sum_{n=1}^{\infty} (n \log n)}{\sum_{n=1}^{\infty} (n \log n)}$$

Taking log on both sides, log [n ≤ log nⁿ log [n ≤ nlog n] O(nlog n)

· Solve the following recurrence relation by method of substitution.

$$T(n) = \sqrt{n} T(\sqrt{n}) + n$$

Dividing both sides by n, $\frac{T(n)}{n} = \frac{T(\sqrt{n})}{\sqrt{n}} + 1$

Putting
$$n = 2^m$$
,

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

Let, $T(2^m) = S(m)$

So, $S(m) = S(m/2) + 1$

From the previous example, we got the time complexity of this type of recurrence relation as $O(\log n)$
 $T(2^m) = O(\log m)$
 $T(2^m) = O(2^m \log m)$
 $T(2^m) = O(n \log \log n)$
 $T(n) = O(n \log \log n)$
 $T(n) = O(n \log \log n)$