

Foundations of Algorithm SCS1308

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Lecture 2



Example of Count: Counting sort

Input: Array T containing n keys in ranges $1..S$

Idea: (Similar to Histogram)

- 1) Maintain the count of number of keys in an auxiliary array U*
- 2) Use counts to overwrite array in place*

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Input T	2	1	2	4	3	1	2
	1	2	3	4			
Aux U	2	3	1	1			
Output T	1	1	2	2	2	3	4

Example : counting sort

- $T = [2, 1, 4, 3, 2]$ and $s = 4$
- **Step 1:** Initialize $U = [0, 0, 0, 0]$
- **Step 2:** Count
 - $T[1]=2 \rightarrow U[2]++ \rightarrow U=[0,1,0,0]$
 - $T[2]=1 \rightarrow U[1]++ \rightarrow U=[1,1,0,0]$
 - $T[3]=4 \rightarrow U[4]++ \rightarrow U=[1,1,0,1]$
 - $T[4]=3 \rightarrow U[3]++ \rightarrow U=[1,1,1,1]$
 - $T[5]=2 \rightarrow U[2]++ \rightarrow U=[1,2,1,1]$
- **Step 3:** Rewrite
→ Sorted $T = [1, 2, 2, 3, 4]$

Algorithm:

Counting-Sort(T , s)

1. for $i = 1$ to s
 $U[i] = 0$

//initialize U $O(s)$

2. for $j = 1$ to n // $n = \text{length}[T]$

3. $U[T[j]] = U[T[j]] + 1$

//Count keys $O(n)$

4. $q = 1$

5. for $j = 1$ to s

6. while $U[j] > 0$

7. $T[q] = j$

8. $U[j] = U[j] - 1$

9. $q = q + 1$

//rewrite T

Barometer operation

$O(n+s)$

Asymptotic Growth Rate

Asymptotic Notation

- Asymptotic notation does not provide an exact running time or space usage for an algorithm, but rather a description of how the algorithm scales with respect to input size.
- A useful tool for comparing the efficiency of different algorithms and for predicting how they will perform on large input sizes.

Big - O (Big-Oh)

- **Upper bound** on the growth rate of an algorithm's running time or space usage.
- Represent **worst case** scenario - the maximum amount of time or space an algorithm may need to solve a problem.
- Eg: What does it mean to say $O(n)$?
 - It means that the running time of the algorithm increases linearly with the input size **n or less**.

Example 1 :

- Find upper bound for $f(n) = 3n + 8$

Solution: $3n + 8 \leq c.g(n)$, for all $n \geq n_0$

$\therefore 3n + 8 = O(n)$ with $c = 4$ and $n_0 = 8$

Example 1 :

- Find upper bound for $f(n) = n^4 + 100n^2 + 50$

Solution: $n^4 + 100n^2 + 50 \leq cg(n)$, for all $n \geq 1$

$\therefore n^4 + 100n^2 + 50 = O(n^4)$ with $c = 151$ and $n_0 = 1$

Does $5n+2 \in O(n)$?

Proof: From the definition of Big Oh, there must exist $c > 0$ and integer $N > 0$ such that $0 \leq 5n+2 \leq cn$ for all $n \geq N$.

Dividing both sides of the inequality by $n > 0$ we get:

$$0 \leq 5 + 2/n \leq c.$$

- $2/n$ (> 0) becomes smaller as n increases
- For instance, let $N = 2$ and $c = 6$

There are many choices here for c and N .

Does $n^2 \in O(n)$?

Does $n^2 \in O(n)$? No.

We will **prove by contradiction** that the definition cannot be satisfied.

- Assume that $n^2 \in O(n)$. From the definition of Big Oh, there must exist $c > 0$ and integer $N > 0$ such that $0 \leq n^2 \leq cn$ for all $n \geq N$.
- **Divide** the inequality by $n > 0$ to get $0 \leq n \leq c$ for all $n \geq N$.
- $n \leq c$ cannot be true for any $n > \max\{c, N\}$. This contradicts the assumption. Thus, $n^2 \notin O(n)$.

Are they true? Why or why not?

- $1,000,000 n^2 \in O(n^2) ?$

- True

- $(n - 1)n / 2 \in O(n^2) ?$

- True

- $n / 2 \in O(n^2) ?$

- True

- $\lg(n^2) \in O(\lg n) ?$

- True

- $n^2 \in O(n) ?$

- False

Omega notation (Ω)

- Provides a **lower** bound on the growth rate of an algorithm's running time or space usage.
- Represent **best** case scenario – minimum amount of time or space an algorithm may need to solve a problem.
- Eg: What does it mean to say $\Omega(n)$?
 - It means that the running time of the algorithm increases linearly with the input size **n or more**.

Example 3 :

- Find lower bound for $f(n) = 5n^2$

Solution: $\exists c, n_0$ Such that: $0 \leq cn^2 \leq 5n^2 \Rightarrow cn^2 \leq$

$5n^2 \Rightarrow c = 5$ and $n_0 = 1$

$\therefore 5n^2 = \Omega(n^2)$ with $c = 5$ and $n_0 = 1$

Are they true?

- $1,000,000 \cdot n^2 \in \Omega(n^2)$ why /why not?
 - true
- $(n - 1)n / 2 \in \Omega(n^2)$ why /why not?
 - true
- $n / 2 \in \Omega(n^2)$ why /why not?
 - (false)
- $\lg(n^2) \in \Omega(\lg n)$ why /why not?
 - (true)
- $n^2 \in \Omega(n)$ why /why not?
 - (true)

Theta notation (Θ)

- Provides **both an upper and lower bound** on the growth rate of an algorithm's running time or space usage.
- Represents the **average-case** scenario, i.e., the amount of time or space an algorithm typically needs to solve a problem
- Eg: What does it mean to say $\Theta(n)$?

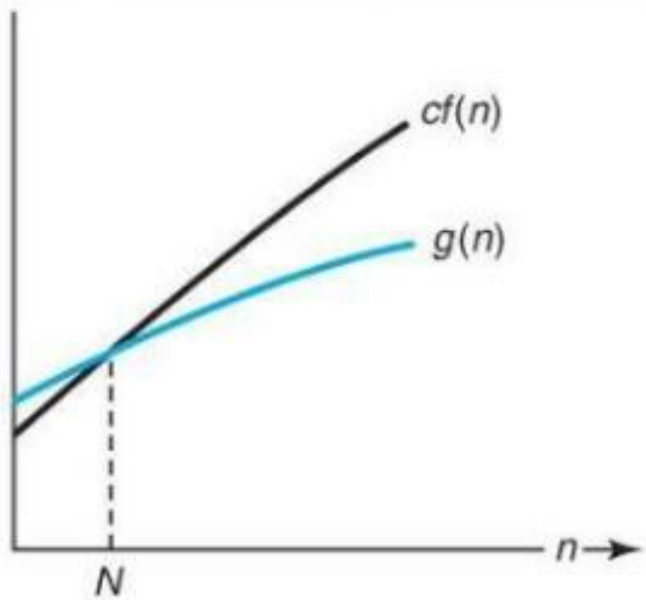
Then it means that the running time of the algorithm increases linearly with the input size n .

Example 4 :

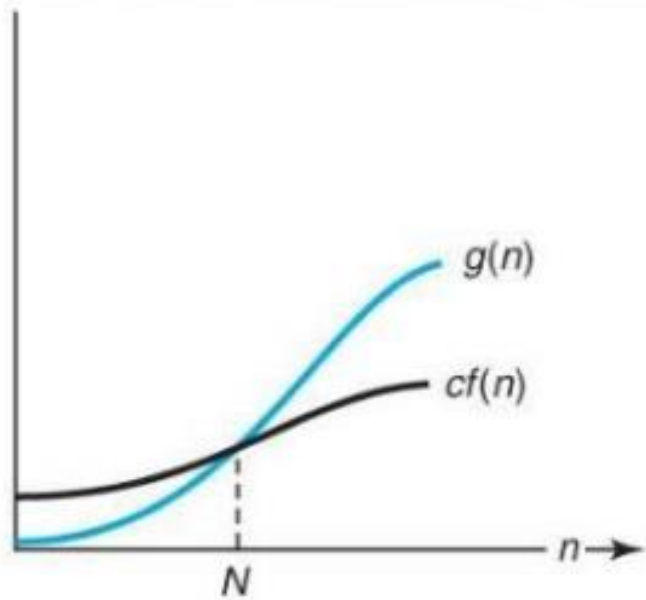
- Find Θ bound for $f(n) = \frac{n^2}{2} - \frac{n}{2}$

we have $c_1 n^2 \leq f(n) \leq c_2 n^2$ for all $n \geq n_0$, so $f(n) = \Theta(n^2)$

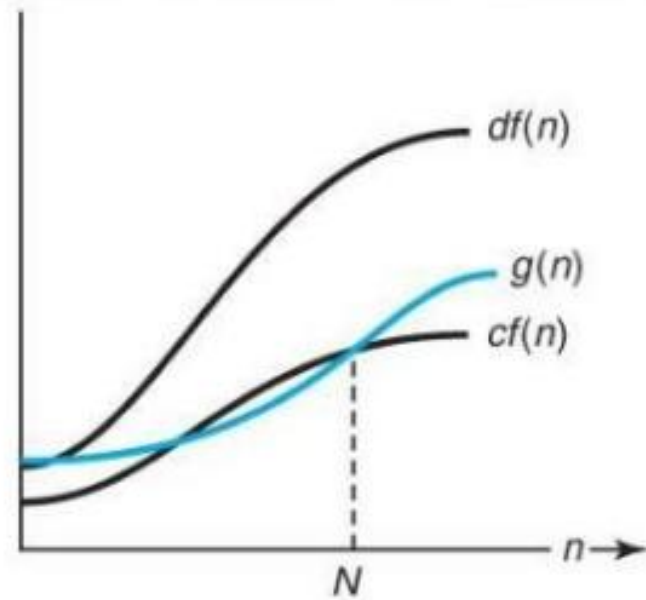
For $c_1 = \frac{1}{4}$, $c_2 = \frac{1}{2}$, $n_0 = 2$



(a) $g(n) \in O(f(n))$



(b) $g(n) \in \Omega(f(n))$



(c) $g(n) \in \theta(f(n))$

Illustration : Big O, Omega and Theta

small o

- $o(f(n))$ is the set of functions $g(n)$ which satisfy the following condition:
For *every* positive real constant c , there exists a positive integer N , for which
$$g(n) \leq cf(n) \text{ for all } n \geq N$$

Big O vs. Small o

Big O

- $f(n)=O(g(n))$ means $f(n)$ grows at most as fast as $g(n)$

$$f(n) \leq C \cdot g(n) \quad \text{for all } n \geq n_0,$$

- Big O gives an upper bound on $f(n)$
- $f(n)$ grow as fast as $g(n)$ but not faster.

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \leq C, \\ C > 0.$$

Small o

- $f(n) = o(g(n))$ means $f(n)$ grows strictly slower than $g(n)$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$$

- Small o gives a strict upper bound
- $f(n)$ is negligible compared to $g(n)$ as $n \rightarrow \infty$.

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0.$$

small omega

- $\omega(f(n))$ is the set of functions $g(n)$ which satisfy the following condition:

For *every* positive real constant c , there exists a positive integer N , for which

$$g(n) \geq cf(n) \text{ for all } n \geq N$$

Omega Ω vs. Small ω

Omega Ω

- $f(n) = \Omega(g(n))$ means $f(n)$ grows at least as fast as $g(n)$

$$f(n) \geq C \cdot g(n) \quad \text{for all } n \geq n_0,$$

- Omega gives a lower bound on $f(n)$
- $f(n)$ grow as fast or at the same rate as $g(n)$ but not slower.

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \leq C, \\ C > 0.$$

Small ω

- $f(n) = \omega(g(n))$ means $f(n)$ grows strictly faster than $g(n)$

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty$$

- Small ω gives a strict lower bound
- $f(n)$ must grow strictly faster than $g(n)$, $g(n)$ becomes negligible compared to $f(n)$ as $n \rightarrow \infty$.

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0.$$

Analogy between asymptotic comparison of functions and comparison of real numbers.

$$f(n) = \mathbf{O}(g(n)) \quad \approx \quad a \leq b$$

$$f(n) = \mathbf{\Omega}(g(n)) \quad \approx \quad a \geq b$$

$$f(n) = \mathbf{\Theta}(g(n)) \quad \approx \quad a = b$$

$$f(n) = \mathbf{o}(g(n)) \quad \approx \quad a < b$$

$$f(n) = \mathbf{\omega}(g(n)) \quad \approx \quad a > b$$

$f(n)$ is asymptotically smaller than $g(n)$ if $f(n) = \mathbf{o}(g(n))$

$f(n)$ is asymptotically larger than $g(n)$ if $f(n) = \mathbf{\omega}(g(n))$

Order of Algorithm

- Property

- Complexity Categories:

$$\begin{array}{ccccccc} \theta(\lg n) & \theta(n) & \theta(n \lg n) & \theta(n^2) & \theta(n^j) & \theta(n^k) & \theta(a^n) \\ \theta(b^n) & \theta(n!) & & & & & \end{array}$$

Where $k > j > 2$ and $b > a > 1$. If a complexity function $g(n)$ is in a category that is to the left of the category containing $f(n)$, then $g(n) \in o(f(n))$

Thank you