

Introduction to Algorithms

Prasanta K. Jana, IEEE Senior Member



**Department of Computer Science and Engineering
Indian Institute of Technology (ISM), Dhanbad
E-mail: prasantajana@yahoo.com**



Algorithm

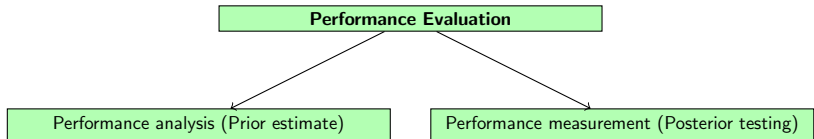


- **Finiteness** (to be terminated after finite number of steps)
- **Definiteness** (Instructions to be clear and unambiguous)
- **Effectiveness** (Instructions to be very basic)



Why to learn this subject ?

- Space Complexity
- Time Complexity



- Counting Method:

Any comment $\leftarrow 0$

An assignment statement $\leftarrow 1$

Every iterative statement (e.g., for) $\leftarrow 1$

Algorithm 1 $\text{Sum}(a, n)$

```
1: begin
2:    $sum \leftarrow 0.0$ 
3:    $count \leftarrow count + 1$ 
4:   for  $i = 1$  to  $n$ 
5:      $count \leftarrow count + 1$ 
6:      $sum \leftarrow sum + a[i]$ 
7:      $count \leftarrow count + 1$ 
8:   end for
9:    $count \leftarrow count + 1$ 
10:   $count \leftarrow count + 1$ 
11:  return  $sum$ 
12: end
```

Total count $\leftarrow 2n + 3$

Algorithm 2 Sum(a, n)

```
1: begin
2:    $count \leftarrow count + 1$ 
3:   for  $i = 1$  to  $n$ 
4:      $count \leftarrow count + 1$ 
5:      $count \leftarrow count + 1$ 
6:   end for
7:    $count \leftarrow count + 1$ 
8:    $count \leftarrow count + 1$ 
9: end
```

Total count $\leftarrow 2n + 3$



Algorithm 3 $\text{ADD}(a, b, c, m, n)$

```
1: for  $i = 1$  to  $m$ 
2:   for  $j = 1$  to  $n$ 
3:      $c[i, j] \leftarrow a[i, j] + b[i, j]$ 
4:   end for
5: end for
```

Total step count $\leftarrow 2mn + 2m + 1$



Algorithm $\text{sum}(a, n)$	s/e	f	<i>Total steps</i>
1: begin			
2: $s \leftarrow 0.0$	1	1	1
3: for $i = 1$ to n	1	$n + 1$	$n + 1$
4: $s \leftarrow s + a[i]$	1	n	n
5: end for			
6: return s	1	1	1
7: end			

Total steps $\leftarrow 2n + 3$

Asymptotic notations



$O, \Omega, \Theta, o, \omega$

- O [Big “oh”]
 $f(n) = O(g(n))$ iff \exists positive constants c and n_0 s.t.
 $f(n) \leq cg(n) \forall n, n \geq n_0$

Theorem

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

- Ω (Big omega)
- $f(n) = \Theta(g(n))$

Theorem

If $f(n) = a_m n^m + a_{m-1} n^{m-1} + \dots + a_1 n + a_0$ and $a_m > 0$ then $f(n) = \Theta(n^m)$

- $f(n) = o(g(n))$ iff

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

- $f(n) = \omega(g(n))$ iff

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



Show that:

- (I) $5n^2 - 6n = \Theta(n^2)$
- (II) $n! = o(n^n)$
- (III) $2n^22^n + n\log(n) = \Theta(n^22^n)$
- (IV) $n^32^n + 6n^23^n = O(n^32^n)$



- **Purpose:** In an amortized analysis, the time required to perform a sequence of data structure operations is averaged over all the operations performed.
- **Why:** Amortized analysis can be used to show that the average cost of an operation is small, if one averages over a sequence of operations, even though a single operation might be expensive.
- **How does it differ from average case analysis :** It differs from average case analysis in that probability is not involved.



- **Advantage:** It guarantees the average performance of each operation in the worst case.
- **What does amortization means:** it means transforming cost. In an amortized scheme, we change some of the actual cost of an operation to other operations. This reduces the charged cost of some operations and increases that of others.

Common techniques:



- Aggregate method
- Accounting method
- Potential method

The aggregate method



Here, we show that for all n , a sequence of n operations takes worst case time $T(n)$ in total. In the worst case, the average cost or amortized cost, per operation is therefore $T(n)/n$.

An example (STACK OPERATIONS)



- **PUSH(S,x)** requires $O(1)$ costs 1
- **POP(S)** requires $O(1)$ costs 1
- The total cost of a sequence of n **PUSH** and **POP** operations is therefore n .

Therefore, the actual running time of n operations is $\Theta(n)$.



Algorithm 4 MULTIPOP(S, k)

```
1: while not  $STACK - EMPTY(S)$  and  $K \neq 0$ 
2:   POP( $S$ )
3:    $k \leftarrow k - 1$ 
4: end while
```

- The worst case time of MULTIPOP is $O(n)$.
- Therefore, a sequence of n PUSH, POP, and MULTIHOP costs $O(n^2)$.
- **Conclusion:** This bound is not tight.
- We obtain a better upper bound by amortized analysis.
- Amortized cost of an operation $O(n)/n = O(1)$.



- **Problem:** Implementation of a k -bit binary counter that counts upward from 0.

Algorithm 5 INCREMENT(A)

```
1:  $i \leftarrow 0$ 
2: while  $i < \text{length}[A]$  and  $A[i] == 1$ 
3:    $A[i] \leftarrow 0$ 
4:    $i \leftarrow i + 1$ 
5: end while
6: if  $i < \text{length}[A]$  then
7:    $A[i] \leftarrow 1$ 
8: end if
```



Consider the following figure:

Counter	A[7]	A[6]	A[5]	A[4]	A[3]	A[2]	A[1]	A[0]	Total cost
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	1
2	0	0	0	0	0	0	1	0	3
3	0	0	0	0	0	0	1	1	4
4	0	0	0	0	0	1	0	0	7
5	0	0	0	0	0	1	0	1	8
6	0	0	0	0	0	1	1	0	10
6	0	0	0	0	0	1	1	1	11
8	0	0	0	0	1	0	0	0	15
9	0	0	0	0	1	0	0	1	16
10	0	0	0	0	1	0	1	0	18
11	0	0	0	0	1	0	1	1	19
12	0	0	0	0	1	1	0	0	22
13	0	0	0	0	1	1	0	1	23
14	0	0	0	0	1	1	1	0	25
15	0	0	0	0	1	1	1	1	26
16	0	0	0	1	0	0	0	0	31



- $A[0]$ does flip each time INCREMENT is called.
- $A[1]$ flips every other time, a total $\lfloor n/2 \rfloor$ times.
- $A[2]$ flips every fourth time, a total $\lfloor n/4 \rfloor$ times.
- In general, for $i = 0, 1, \dots, \lfloor \log(n) \rfloor$, $A[i]$ flips $\lfloor \frac{n}{2^i} \rfloor$ times in a sequence of n INCREMENT operations on an initially zero counter.
- For $i \geq \lfloor \log(n) \rfloor$, bit $A[i]$ never flips at all.
- Therefore, total no. of flips is $\sum_{i=0}^{\lfloor \log(n) \rfloor} \lfloor \frac{n}{2^i} \rfloor < n \sum_{i=0}^{\infty} \frac{1}{2^i} = 2n$.
- Therefore, worst case for a sequence of n INCREMENT is $O(n)$.
- Hence, amortized cost of each operation is $O(n)/n = O(1)$.

