



Algorithms and Complexity

Algorithm Complexity

Lecturer: Asst. Prof. Dr. Alaa Ahmed Abbood

Lecture 4.

Class 2nd.

Time: 8:30-10:30

Department: Businesses Information Technology (BIT)

Lecture 4

- **Algorithm Complexity**
- **Asymptotic Notations**
- **Definition of "big O"**
- **Standard Method to Prove Big-Oh with Examples**
- **Constant, linear, Logarithmic, and Quadratic time complexity**
- **Definition of "big Omega" and "big Theta"**
- **Analysis of Algorithms**
- **Amortized Time Complexity**



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Algorithm Complexity

1- Algorithmic Complexity :

- Algorithmic complexity is concerned about how fast or slow particular algorithm performs.
- We define complexity as a numerical function $T(n)$ - time versus the input size n .
- We want to define time taken by an algorithm without depending on the implementation details. But you agree that $T(n)$ does depend on the implementation.



Algorithm Complexity. Cont...

- A given algorithm will take different amounts of time on the same inputs depending on such factors as: processor speed, instruction set, disk speed, brand of compiler and etc.
- The way around is to estimate efficiency of each algorithm asymptotically. We will measure time $T(n)$ as the number of elementary "steps" (defined in any way), provided each such step takes constant time.



Algorithm Complexity. Cont...

- Let us consider two classical examples which search an element in a list.

0	1	2	3	4	5	6	7	8	9
2	3	5	7	8	10	12	15	18	20

↑
Low

Best case

↑
Mid

Average case

↑
High

Worse case



- There are three cases
 1. Best case (Omega notation Ω)
 2. Average case (Theta notation Θ)
 3. Worst case (Big O notation)



Constant Time: $O(1)$

- An algorithm is said to run in constant time if it requires the same amount of time regardless of the input size.

Examples:

- array: accessing any element.
- All the operations such as (+, -, *, /, %, ^, = etc.)
- If – else statement.
- Any program statement.



Constant Time: $O(1)$

Examples: consider the following code :-

```
{  
int n; //  $O(1)$   
int sum; //  $O(1)$   
  
    {  
        Sum =  $n*(n+1)/2$  //  $O(1)$   
    }  
Print sum //  $O(1)$   
  
}
```

Therefore the worst case of this code = $O(1)$.



Linear Time: $O(n)$

Examples: consider the following code :-

```
{  
int n;  
int i; //  $O(1)$   
i=0; //  $O(1)$ 
```

```
    {  
    for (i=0, i<n, n++) //  $O(n)$ 
```

Big $O = 1+n$

```
    }
```

$O(n)$

```
Print i ; //  $O(1)$ 
```

```
}
```



Linear Time: $O(n)$

Examples: consider the following code :-

```
{  
int n;  
int i; //  $O(1)$   
i=0; //  $O(1)$   
  
    for (i=0, i<n, n++) { //  $(n)$   
  
        Print i } //  $O(1)$   
        for ( int j=0; j<n; j++) //  $(n)$   
        for (int k=0; k<n; k++) //  $(n)$   
        for ( intl=0; l<n; l++) //  $(n)$   
  
}
```

$$\text{Big } O = 1 + n + n * n * n$$

$$O(n) = 1 + n + n^3$$

$$O(n) = n^3$$



Logarithmic Time: $O(\log n)$

Examples: consider the following code :-

```
{  
int n;  
int i; //  $O(1)$   
i=1; //  $O(1)$ 
```

```
    for (i, i<n, i=i*2) { //  $\log(n)$ 
```

```
        Print i }  
    }
```

Big O = $1 + \log_2(n)$

**Note: that only if
the increment * or /**



Logarithmic Time: $O(\log n)$

Examples: consider the following code :-

```
{  
int i, j;  
i=j=0; //  $O(1)$ 
```

```
    for (i, i<n, i++) { //(n)
```

```
        for ( j; j<n; j=j/3) //(log3 n)
```

```
        Print i +j } //  $O(1)$ 
```

```
}
```

Big O= $1+n * \log_3 n$

Big O= $n \log_3 n$



Logarithmic Time: $O(\log n)$

Examples: consider the following code :-

```
{  
int i, j, k;  
i=j=0; //  $O(1)$ 
```

```
    for (i, i<n, i++) { //(n)  
        for ( j; j<n; j=j++) //(n)  
            for ( k; j<n; k=k*2)  $\log_2 n$ 
```

Big $O = 1 + n * n * \log_2 n$

$O = n^2 \log n$

```
Print i +j +k} //  $O(1)$ 
```

```
}
```



Logarithmic Time: $O(\log n)$

Examples: consider the following code :-

```
{  
int i, j, k;  
i=j=0; //  $O(1)$ 
```

```
    for (i, i<n/2, i++) { //  $(n/2)$   
        for ( j; j<n; j=j/2) //  $\log_2 n$   
            for ( k; j<n; k=k*2)  $\log_2 n$ 
```

```
    Print i +j +k} //  $O(1)$ 
```

```
}
```

Big $O = n/2 * n * \log_2 n$

$O = n * \log_2 n * \log_2 n$

$O = n * \log_2 n^2$



summary

- The term analysis of algorithms is used to describe approaches to the study of the performance of algorithms.
- ❖ In this course we will perform the following types of analysis:
- **The worst-case runtime complexity of the algorithm** is the function defined by the maximum number of steps taken on any instance of size a .
- **The best-case runtime complexity of the algorithm** is the function defined by the minimum number of steps taken on any instance of size a .
- **The average case runtime complexity of the algorithm** is the function defined by an average number of steps taken on any instance of size a .





THANK YOU