# Stanford Divide & Conquer

**Analysis of Algorithms** 

## Question

What should be the CRITERIA for analysis of Algorithms?

- How much time does the algorithm take to perform the procedure?
- The procedure or algorithm must be time efficient.
- The algorithm must be fast.
- After analyzing the time we get the Time Function.
- We Do Not get time in hours, minutes, seconds, milliseconds.....

# **Space Complexity**

How much memory or space the algorithm or procedure will consume?

## Question

Is there any other CRITERIA for analysis of Algorithms?

Time and Space complexities are the major criterias on which the algorithms are analyzed.

There can be **several** other criterias as well depending on the requirements.

#### **Network Transfer**

How much data would be transferred? Is algorithm transferring larger size of data or can it be reduced?

#### **Power Consumption**

In the era of increasingly handheld devices, how much power the algorithm is consuming can also an important criteria.

The criterias you need to analyze depends on the project and its requirements. Some criterias for analysis of algorithms are as follows.

- Time Complexity
- Space Complexity
- Security
- Network Transfer
- Bandwidth Consumption
- Power Consumption

- Latency
- Reliability
- Scalability
- Cache Efficiency
- Concurrency
- I/O Operations

## **Time Complexity**

We calculate Time complexity in mathematical notations rather than in absolute time due to some of the following reasons.

- Independence from Input size
- Predictive Power
- Machine and Environment Variability
- Consistency Across Implementations

# **Time Complexity**

Some common mathematical notations to calculate Time complexity are as follows.

- Big O Notation (O)
- Big Omega Notation (Ω)
- Big Theta Notation (Θ)
- Little O Notation (o)
- ▶ Little Omega Notation (□

# **Time Complexity**

#### **Big O Notation (O)**

- Big O Notation (O) focuses on worst case complexity of an algorithm.
- Big O gives the upper bound on the growth rate of an algorithm.
- E.g. For a sorting algorithm, Big O shows the longest possible time it might take.
- We prioritize the term that grows the fastest as the input size increases.

# **Time Complexity**

## Big O Notation (O)

- Big O Notation ignores constant and less significant terms.
  - O(3n \* 1000000000) = ?
  - $\circ$  O(5000n<sup>2</sup> + 3n<sup>3</sup> + 10<sup>9</sup>) = ?
  - $\circ$  **O**(n ÷ 2) = ?
  - O(n ÷ 1000000000) = ?

# **Time Complexity**

#### Big O Notation (O)

- Focuses on the worst case.
- It represents upper bound of an algorithm's time or space complexity.
- The algorithm performs at most linear time in the worst case.

#### Big Omega Notation $(\Omega)$

- Focuses on the best case.
- It represents lower bound of an algorithm's time or space complexity.
- The algorithm performs at least a constant time, no matter the input size.

# **Time Complexity**

#### Big Theta Notation (Θ)

- Focuses on the average case.
- It represents tight bound of an algorithm's time or space complexity.
- It gives both the upper bound and lower bound of the algorithm performance.
- We represent theta notation when lower and upper bound are same or when worst or best cases are same.
- We do not express theta when upper and lower bounds are different.
- Example: ?

## **Time Complexity**

```
def print_elements(arr):
    # Iterate over the list and print each element
    for element in arr:
        print(element) # Constant time operation
```

Worst case: O(n)

Best case:  $\Omega(n)$ 

Overall (tight bound):  $\Theta(n)$ 

## **Time Complexity**

```
• • •
def linear_search(arr, target):
    if arr[0] == target:
        return 0
    for i in range(1, len(arr)):
        if arr[i] == target:
            return i
```

Worst case: **O(n)** 

Best case:  $\Omega(1)$ 

# **Time Complexity**

## **Time Complexity as a Function**

After Time Complexity analysis we get a function of time.

- Time function tells us how the algorithm behaves as the input grows.
- It describes the rate of growth based on the input size (n).
- f(n) = O(n): The algorithm runs in linear time.
- $T(n) = O(n^2)$ : The algorithm runs in quadratic time.
- T(n) = O(1): The algorithm runs in constant time.

# **Time Complexity**

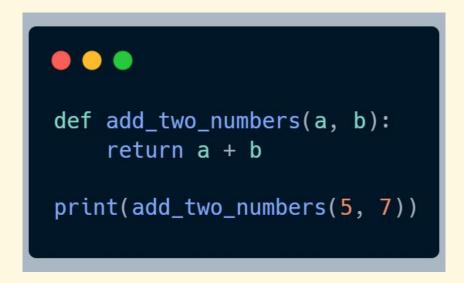
Some common Time Complexities are as follows.

- Constant O(1)
- Logarithmic O(log n)
- Linear O(n)
- Linearithmic O(n log n)

- Quadratic O(n²)
- Cubic O(n<sup>3</sup>)
- Exponential O(2<sup>n</sup>)
- Factorial O(n!)

## **Time Complexity**

**Constant O(1)** 



# **Time Complexity**

Linear O(n)

```
def sum_elements(arr):
    total = 0
    for num in arr:
        total += num
    return total

result = sum_elements([100, 50, 90, 80])
print(result)
```

# **Time Complexity**

## Logarithmic O(log n) - Exponents & Logs

$$q^4 = q \cdot q \cdot q \cdot q = 16$$

$$2^4 = 2 \cdot 2 \cdot 2 \cdot 2 = 16$$

- $2^{x}$  = 16. What is **x** here ?
- $2^{x}$  = 1024. What is **x** here ?
- $2^{x}$  = 1000000000. What is **x** here ?

- Base
- Exponents
- Logs

## **Time Complexity**

## **Logarithmic O(log n) - Exponents & Logs**

 $Log_3 81 = x$  What is **x** here?



$$3^{x} = 81$$

Logarithmic form		<b>Exponential form</b>	
$\log_2(8) = 3$	$\iff$	$2^3 = 8$	
$\log_3(81) = 4$	$\iff$	$3^4 = 81$	
$\log_5(25) = 2$	$\iff$	$5^2 = 25$	

# **Time Complexity**

## Logarithmic O(log n) - Exponents & Logs

PROBLEM 1

Which of the following is equivalent to  $2^5 = 32$ ?

Choose 1 answer:

- (B)  $\log_5(2) = 32$
- ©  $\log_{32}(5) = 2$

# **Time Complexity**

## Logarithmic O(log n) - Exponents & Logs

PROBLEM 2

Which of the following is equivalent to  $5^3 = 125$ ?

Choose 1 answer:

- (B)  $\log_5(125) = 3$

# **Time Complexity**

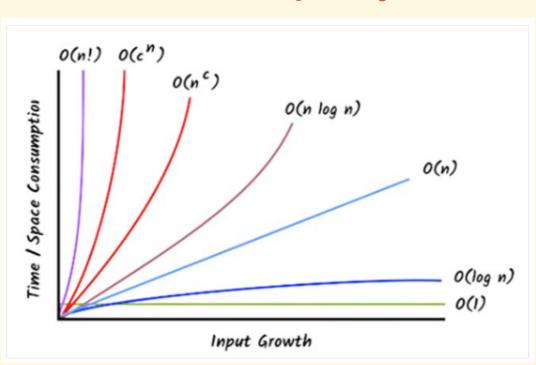
**Binary Search** 

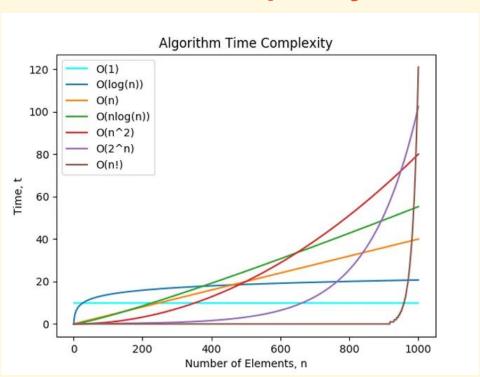
Search the number 7 in the array Mid (7 > 5, consider right half) High 10 8 9 (7 < 8, consider left half) Mid Low 9 (7 > 6, consider right half) Low = Mid = 5 High 8 9 10 Low = Mid = High=6 (7 is present at the index 6) 10

**Logarithmic O(log n)** 

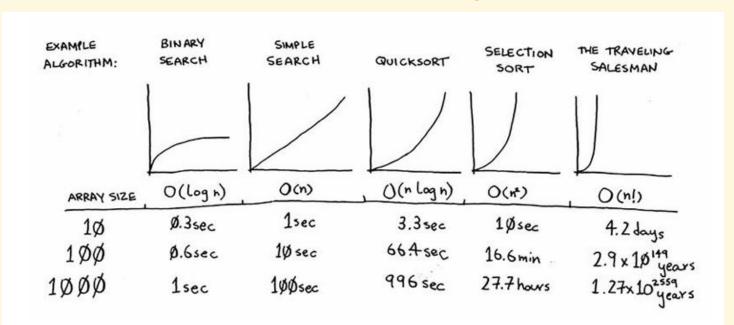
- Binary Search

Orders of Growth (Good to Bad)		
O(1)	Constant	
O(log n)	Logarithmic	
O(n)	Linear	
O(n log n)	Linearithmic	
O(n²)	Quadratic	
O(n³)	Cubic	
O(2 <sup>n</sup> )	Exponential	
O(n!)	Factorial	





## **Time Complexity**



Estimates based on a slow computer that performs 10 operations per second

Time Complexities in increasing order of growth.

$$O(1) < O(\log n) < O(\sqrt{n}) < O(n) < O(n \log n) < O(n^2) < O(n^3) < O(n^{100}) < \dots$$
 $< O(2^n) < O(3^n) < O(1000^n) < \dots < O(n!) < O(n^n)$ 

- Each next item will grow faster than the previous one
- Slowest growing to fastest growing.
- O(1) grows the slowest, O(n<sup>n</sup>) grows the fastest.

Time Complexities in decreasing order of growth.

$$O(n^n) > O(n!) > O(1000^n) > O(3^n) > O(2^n) > O(n^{100}) > O(n^3) > O(n^2) > O(n \log n) > O(n) > O(\sqrt{n}) > O(\sqrt{n}) > O(\log n) > O(1)$$

- Each next item will grow slower than the previous one.
- Fastest growing to slowest growing.
- O(n<sup>n</sup>) grows the fastest, O(1) grows the slowest.

## Resources

<u>Datacamp - Understanding Big O Notation</u>

Khan Academy - Understanding Logarithms

Khan Academy - Logarithms & Exponentials in Practice

