جامعة طرابلس ـ كلية تقنية المعلومات

Design and Analysis Algorithms

تصميم و تحليل خوارزميات

ITGS301

المحاضرة الثانية: Lecture 2

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Order of growth

The fundamental reason is that for large values of *n*, any function that contains an n^2 term will grow faster than a function whose leading term is *n*. The **leading term** is the term with the highest exponent.

we expect an algorithm with a smaller leading term to be a better algorithm for large problems, but for smaller problems, there may be a **crossover point** where another algorithm is better.

An **order of growth** is a set of functions whose asymptotic growth behavior is considered equivalent. For example, $2n$, $100n$ and $n + 1$ belong to the same order of growth, which is written $O(n)$ in **Big-Oh notation** and often called **linear** because every function in the set grows linearly with *n*.

What is Order of Growth?

How the **time/space complexity** of an algorithm **grows/changes** with the **input size**

		حجم المدخلات					
نوع معدل النمو	**معدل النمو**	**n**	**...**	**3**	**2**	**1**	**وقت الخوارزمية**
(Constant) ثابت	1	2	...	2	2	2	وقت الخوارزمية (A)
(Linear) خطي	n	2n	...	6	4	2	وقت الخوارزمية (B)
أسي (Exponential)	c^n	2^n	...	8	4	2	وقت الخوارزمية (K)

معدل تغير وقت أو مساحة الخوارزمية مع تغير حجم المدخلات

What is Order of Growth?

Algorithm 30 Minimum and Maximum Elements

Input: An array $A[1..n]$ of n elements.
Output: The minimum and maximum elements in A

```
min ← A[1]
max ← A[1]
for i ← 2 to n do
    if (A[i] < min) then
        min ← A[i]
    end if
    if (A[i] > max) then
        max ← A[i]
    end if
end for
return (min, max)
```

Algorithm 29 Minimum and Maximum Elements

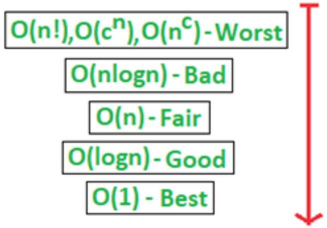
Input: An array $A[1..n]$ of n elements sorted in ascending order.
Output: The minimum and maximum elements in A

```
min ← A[1]
max ← A[n]
return (min, max)
```

Orders of Common Functions

A list of classes of functions that are commonly encountered when analyzing algorithms.

constant	$O(1)$
logarithmic	$O(\log_2 N)$
Linear	$O(N)$
N log n	$O(n \log_2 N)$
Quadratic	$O(N^2)$
Cubic	$O(N^3)$
Exponential	$O(2^n)$
Factorial	$O(n!)$



$$O(1) < O(\log n) < O(n) < O(n \log n) < O(n^2) < O(n^3) < O(2^n)$$

Order of growth

The following table shows some of the orders of growth that appear most commonly in algorithmic analysis.

For the logarithmic terms, the base of the logarithm doesn’t matter; changing bases is the equivalent of multiplying by a constant, which doesn’t change the order of growth.

Similarly, all exponential functions belong to the same order of growth regardless of the base of the exponent.

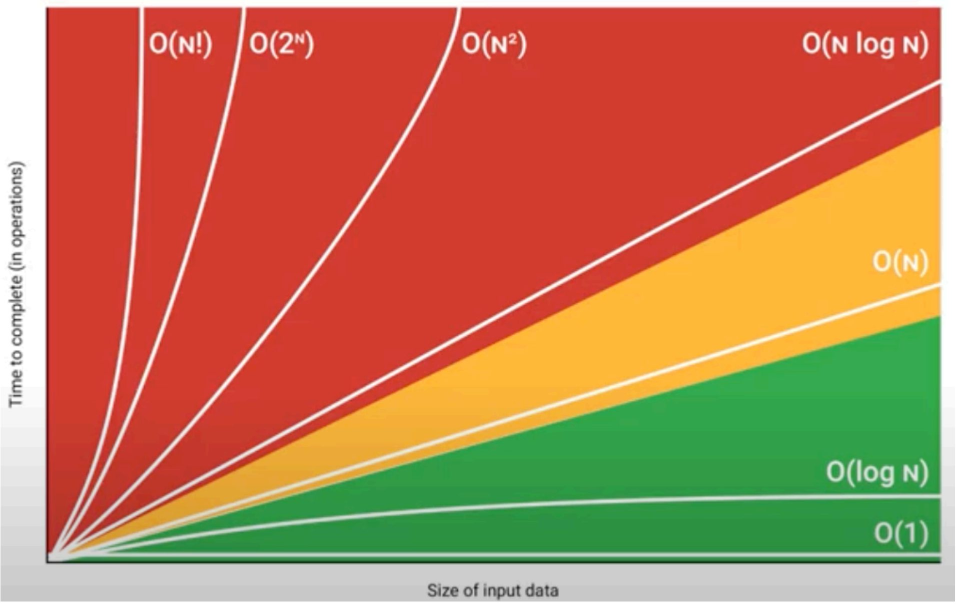
Exponential functions grow very quickly, so exponential algorithms are only useful for small problems.

Order of growth

Name	Function
Constant	c
Double Logarithmic	$\log \log n$
Logarithmic	$\log n$
Fractional Power	$n^c, 0 < c < 1$
Linear	$O(n)$
Loglinear	$n \log n$ and $\log n!$
Quadratic	n^2
Polynomial	$n^c, c > 1$
Exponential	$c^n, c > 1$
Factorial	$n!$
Super Exponential	n^n

Common order-of-growth classifications Running time complexity

	constant	*logarithmic*	*linear*	*N-log-N*	*quadratic*	*cubic*	*exponential*
n	**O(1)**	**O(log *n*)**	**O(*n*)**	**O(*n* log *n*)**	**O(n^2)**	**O(n^3)**	**O(2^n)**
1	1	1	1	1	1	1	2
2	1	1	2	2	4	8	4
4	1	2	4	8	16	64	16
8	1	3	8	24	64	512	256
16	1	4	16	64	256	4,096	65536
32	1	5	32	160	1,024	32,768	4,294,967,296
64	1	6	64	384	4,069	262,144	1.84×10^{19}



Exercise 1

Arrange the functions in increasing asymptotic order

(a) $n^{1/3}$
(b) e^n
(c) $n^{7/4}$
(d) $n \ \log n$
(e) 1.0000001^n

n	n log2(n)	n^(7/4)
2	2	3
4	8	11
8	24	38
16	64	128
32	160	431
64	384	1448

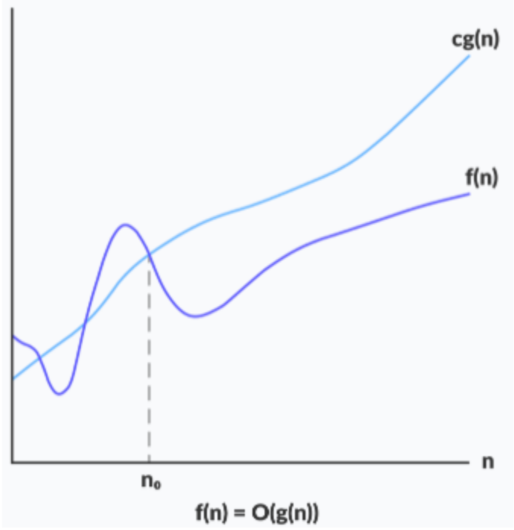
O-notation (Big-Oh)

- Big O Notation (Big-Oh)

Definition: Let f(n) , g(n) be functions, we say f(n) is of order g(n) if there is a constant c>0 such that $n >= n_0$

$$f(n) = O(g(n))$$

$$\text{if } f(n) <= C.g(n) \text{ for all } c,\ n_0 > 0\ ,\ n > n_0.$$



g(n) is asymptotic upper bound for f(n)

Note That:

- we use O-notation to provide an upper bound on the time for any input.
- the worst case running time of an algorithm is upper bound on the time for any input.
- the worst case running time gives us guarantee that the algorithm will never take any longer.

Example #1:

let f(n) = n+ 5 and g(n) = n show that f(n) = O(g(n)) choose c=6.

answer:

f(n) = O(g(n)) if f(n) <= c.g(n) for c,n_0 > 0

n+5 <= c.n

n+5 <= 6n

The condition has been proofed for any n_0 > 0

f(n) = O(n)

Example #2

Prove that the running time of $f(n) = 3n^2 + 10n$ is $O(n^2)$.

Proof:

by big oh definition

$$f(n) = O(n^2) \text{ if } f(n) <= C.g(n) \text{ for } c,n_0 > 0$$

$$3n^2 + 10n <= c.n^2$$

$$3 + 10/n <= c$$

when $n_0 => 1$ then

$$3+ 10 <= c$$

$$13 <= c$$

The condition has been proofed when c = 13 when n=1

Theory

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

when a function is sum of several terms , its order of growth is determined by the fastest growth term.

Proof

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

$f(n) = O(n^m)$ if $f(n) <= c.g(n)$ for $c, n_0 > 0$

$$| a_m n^m + a_{m-1} n^{m-1} + \dots + a_1 n + a_0 | <= c.n^m$$

$$(| a_m n^m + a_{m-1} n^{m-1} + \dots + a_1 n + a_0 |) / n^m <= c$$

when $n_0 = 1$

$$| a_m + a_{m-1} + \dots + a_1 + a_0 | <= c$$

.: $f(n) = O(n^m)$ when $c >= | a_m + a_{m-1} + \dots + a_1 + a_0 |$

The condition has been proofed.

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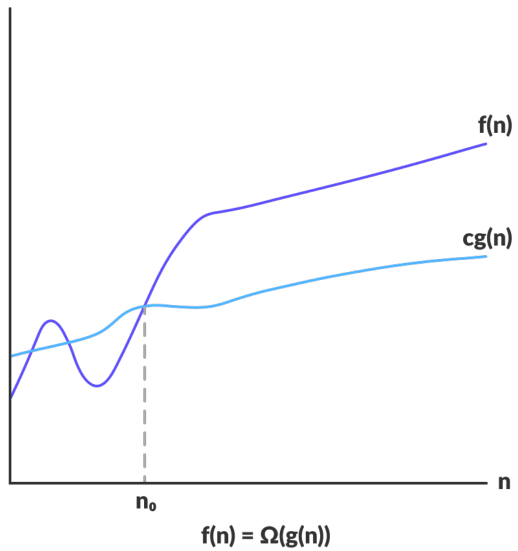
Ω Notation (Big Omega)

Ω Notation

Given two functions $f(n)$ and $g(n)$, we say that $f(n)$ is $\Omega(g(n))$ if there exists positive constants $n0$ and and c such that:

$$f(n) \geq c\, g(n) \quad \forall\, n \geq n_0$$



Example #1

show that $f(n) = 5n^2$ is $\Omega(n^2)$ when c=5 and $n_0=1$.

answer:

$f(n) = \Omega(g(n))$ if $f(n) => c.g(n)$ for $c, n_0 > 0$

$5n^2 => c.n^2$

$5n^2 => 5n^2$

when $n_0=1$

5=>5

The condition is true.

Example #2

show that $f(n) = n^2$ is $\Omega(n)$ when c= 3

answer:

$f(n) = \Omega(g(n))$ if $f(n) => c.g(n)$ for $c, n_0 > 0$

$n^2 => c.n$

$n^2 => 3n$

when c= 3

$3^2 => 3*3$

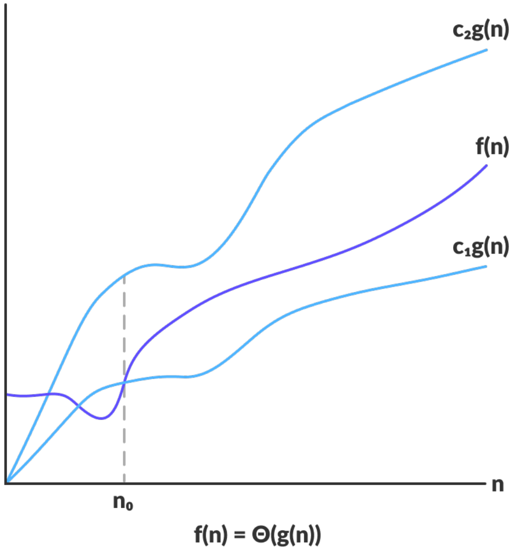
Then $f(n) = \Omega(n)$ when $n_0 = 3$

Θ Notation (Big Theta)

Θ Notation

Given two functions $f(n)$ and $g(n)$, we say that $f(n)$ is $\Theta(g(n))$ if there exists positive constants $n0$, $c1$ and $c2$ such that:

$$\forall\, n \geq n_0, c_1\, g(n) \leq f(n) \leq c_2\, g(n)$$



Example #1

let $f(n) = 3n+2$, $g(n) = n$ show that $f(n) = \Theta(g(n))$ when $c_1 = 3$, $c_2 = 4$.

answer:

$f(n) = \Theta(g(n))$ if $C_1.g(n) <= f(n) <= C_2 .g(n)$

$$3n <= 3n+2 <= 4n$$

when n=2

$$6 <= 8 <= 8$$

the condition has been proofed when c=3,c=4 for all n>1

$\therefore f(n) = \Theta(g(n))$

$f(n) = \Theta(n)$

Note That:

- $f(n) = \Theta(g(n))$ is both upper and lower bound on f(n), this means that the worst and the best case require the same amount of time with in constant factor.

- the Θ-notation called a tight bound.

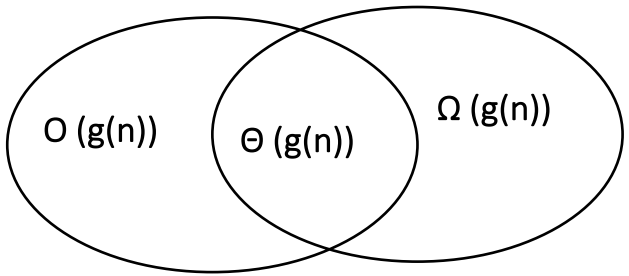
Theory:

For any 2 functions f(n) and g(n) we have $f(n) = \Theta(g(n))$ if and only if $f(n) = O\ (g(n))$ and $f(n) = \Omega\ (g(n))$.

Big O (O()) describes the **upper bound** of the complexity.

Omega (Ω()) describes the **lower bound** of the complexity.

Theta (Θ()) describes the **exact bound** of the complexity.



Exercise 2

Write True or False :

$$T(n) = 5n^3 + 2n^2 + 4 \log n$$

1. $T(n) \in O(n^4)$
2. $T(n) \in O(n^2)$
3. $T(n) \in \Theta(n^3)$
4. $T(n) \in O(\log n)$
5. $T(n) \in \Theta(n^4)$
6. $T(n) \in \Omega(n^2)$

The End .