
Algorithm Analysis

Algorithm

- An algorithm is a finite set of instructions that, if followed, accomplishes a particular task. In addition, all algorithms must satisfy the following criteria:
 1. **Input:** Zero or more quantities are externally supplied.
 2. **Output:** At least one quantity is produced.
 3. **Definiteness:** Each instruction is clear and unambiguous.
 4. **Finiteness:** If we trace out the instructions of an algorithm, then for all cases, the algorithm terminates after a finite number of steps.
 5. **Effectiveness:** Every instruction must be very basic so that it can be carried out, in principle, by a person using only pencil and paper. It is not enough that each operation be definite as in criterion 3; it also must be feasible

Design and Analysis of Algorithms

- **Analysis:** predict the cost of an algorithm in terms of resources and performance
- **Design:** design algorithms which minimize the cost

Algorithmic Performance

- There are *two aspects* of algorithmic performance:
- Time
 - Instructions take time.
 - How fast does the algorithm perform?
 - What affects its runtime?
- Space
 - Data structures take space
 - What kind of data structures can be used?
 - How does choice of data structure affect the runtime?

Why study algorithms and performance?

- Algorithms help us to understand **scalability**.
- Performance often draws the line between what is feasible and what is impossible.
- Algorithmic mathematics provides a **language** for talking about program behavior.
- Performance is the **currency** of computing.
- The lessons of program performance generalize to other computing resources.

The Execution Time of Algorithms

- Each operation in an algorithm (or a program) has a cost.
 - Each operation takes a certain of time.
- **count = count + 1; //** take a certain amount of time, but it is constant
- *A sequence of operations:*

count = count + 1;	Cost: c_1
sum = sum + count;	Cost: c_2

$$\text{Total Cost} = c_1 + c_2$$

The Execution Time of Algorithms

- *Example: Simple If-Statement*

<u>Times</u>	<u>Cost</u>	
if (n < 0)	c1	1
absval = -n	c2	1
else		
absval = n;	c3	1

Total Cost $\leq c1 + \max(c2, c3)$

The Execution Time of Algorithms

- *Example: Simple Loop*

	<u>Cost</u>	<u>Times</u>
<code>i = 1;</code>	<code>c1</code>	1
<code>sum = 0;</code>	<code>c2</code>	1
<code>while (i <= n) {</code>	<code>c3</code>	$n+1$
<code>i = i + 1;</code>	<code>c4</code>	n
<code>sum = sum + i;</code>	<code>c5</code>	n
<code>}</code>		

- Total Cost = $c1 + c2 + (n+1)*c3 + n*c4 + n*c5$
- The time required for this algorithm is proportional to n

The Execution Time of Algorithms

- *Example: Nested Loop*

Times	Cost	
<code>i=1;</code>	<code>c1</code>	1
<code>sum = 0;</code>	<code>c2</code>	1
<code>while (i <= n) {</code>	<code>c3</code>	$n+1$
<code>j=1;</code>	<code>c4</code>	n
<code>while (j <= n) {</code>	<code>c5</code>	
$n*(n+1)$		
<code>sum = sum + i;</code>	<code>c6</code>	$n*n$
<code>j = j + 1;</code>	<code>c7</code>	$n*n$
<code>}</code>		
<code>i = i + 1;</code>	<code>c8</code>	n
<code>}</code>		

- Total Cost = $c1 + c2 + (n+1)*c3 + n*c4 + n*(n+1)*c5 + n*n*c6 + n*n*c7 + n*c8$
 - The time required for this algorithm is proportional to n^2
-

General Rules for Estimation

- **Loops**

- The running time of a loop is at most the running time of the statements inside of that loop times the number of iterations.

- **Nested Loops**

- Running time of a nested loop containing a statement in the inner most loop is the running time of statement multiplied by the product of the sized of all loops.

- **Consecutive Statements**

- Just add the running times of those consecutive statements.

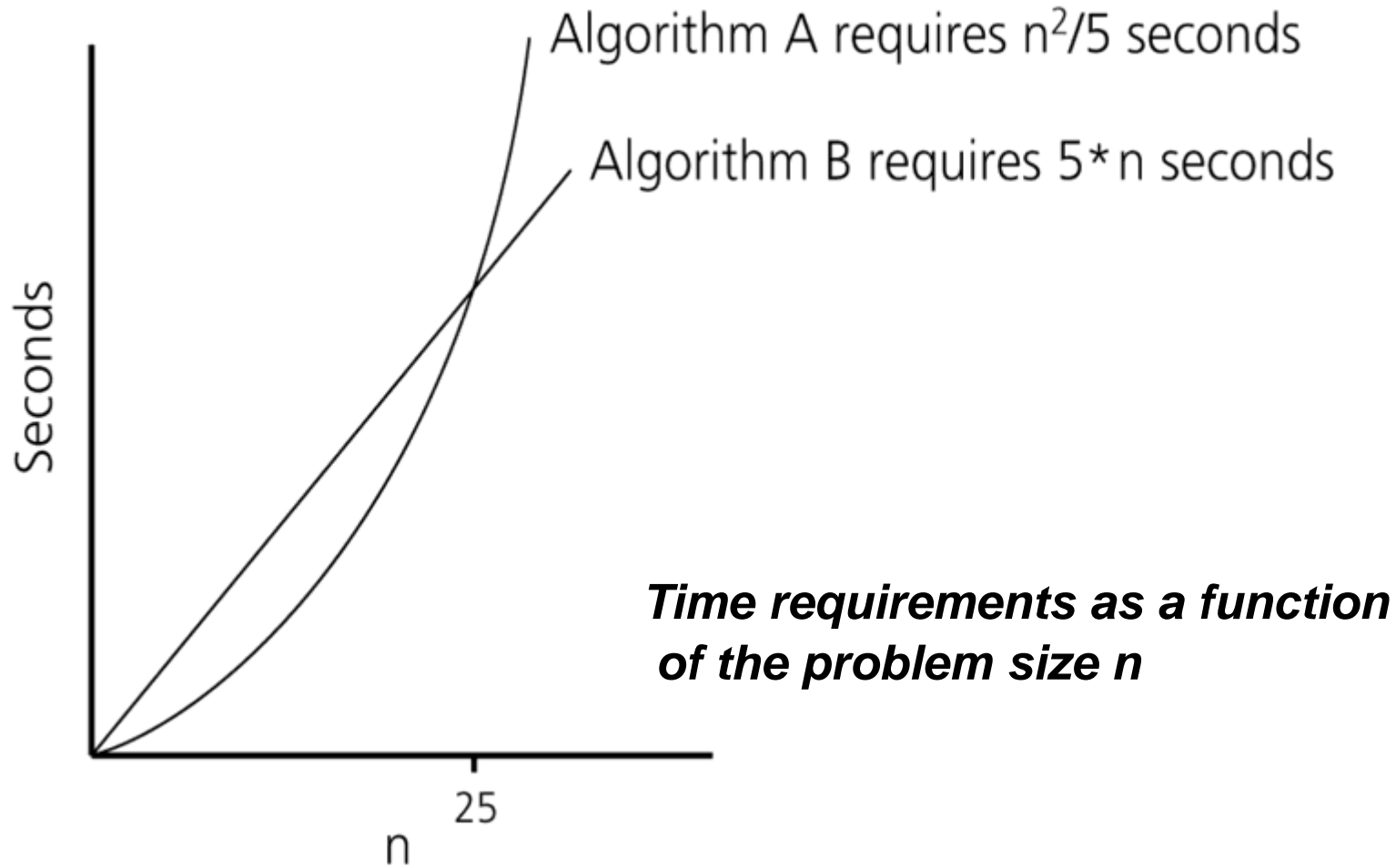
- **If/Else**

- Never more than the running time of the test plus the larger of running times of S1 and S2.

Algorithm Growth Rates

- We measure an algorithm's time requirement as a function of the *problem size*.
 - Problem size depends on the application: e.g. number of elements in a list for a sorting algorithm, the number users for a social network search.
- So, for instance, we say that (if the problem size is n)
 - Algorithm A requires $5 \cdot n^2$ time units to solve a problem of size n .
 - Algorithm B requires $7 \cdot n$ time units to solve a problem of size n .
- The most important thing to learn is how quickly the algorithm's time requirement grows as a function of the problem size.
 - Algorithm A requires time proportional to n^2 .
 - Algorithm B requires time proportional to n .
- An algorithm's proportional time requirement is known as *growth rate*.
- We can compare the efficiency of two algorithms by comparing their growth rates.

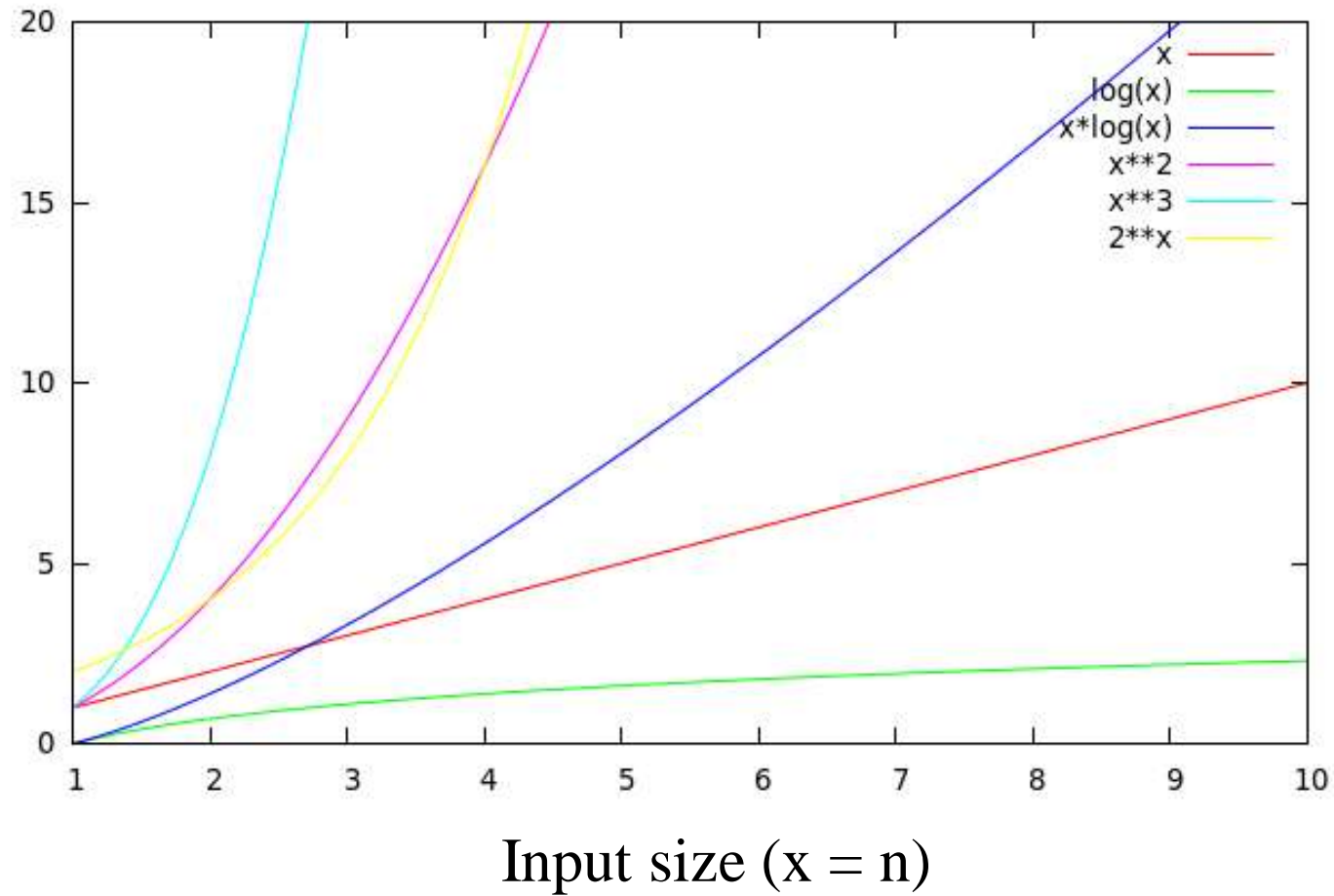
Algorithm Growth Rates



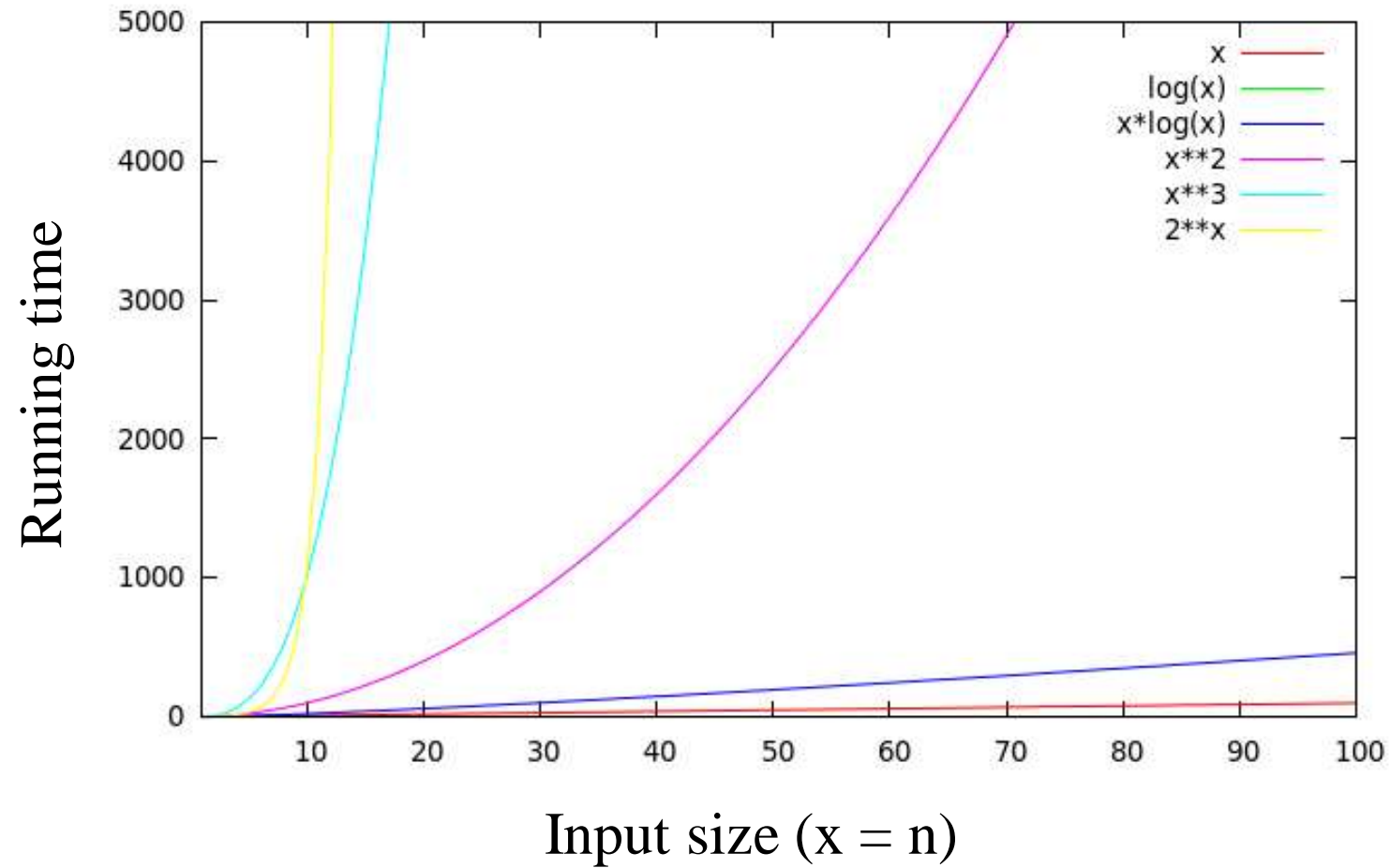
Common Growth Rates

Function	Growth Rate Name
c	Constant
$\log N$	Logarithmic
$\log^2 N$	Log-squared
N	Linear
$N \log N$	Log-linear
N^2	Quadratic
N^3	Cubic
2^N	Exponential

Running Times for Small Inputs



Running Times for Large Inputs



Order-of-Magnitude Analysis and Big O Notation

- If *Algorithm A requires time proportional to $g(n)$* , Algorithm A is said to be order $g(n)$, and it is denoted as $O(g(n))$.
- The function $g(n)$ is called the algorithm's growth-rate function.
- Since the capital O is used in the notation, this notation is called the Big O notation.
- If Algorithm A requires time proportional to n^2 , it is $O(n^2)$.
- If Algorithm A requires time proportional to n , it is $O(n)$.

Definition of the Order of an Algorithm

Definition:

- Algorithm A is order $g(n)$ – denoted as $O(g(n))$
- if constants k and n_0 exist such that A requires no more than $k \cdot g(n)$ time units to solve a problem of size $n \geq n_0$. $\Rightarrow f(n) \leq k \cdot g(n)$ for all $n \geq n_0$
 - The requirement of $n \geq n_0$ in the definition of $O(f(n))$ formalizes the notion of sufficiently large problems.
 - In general, many values of k and n can satisfy this definition.

Order of an Algorithm

- If an algorithm requires $f(n) = n^2 - 3*n + 10$ seconds to solve a problem size n . If constants k and n_0 exist such that

$$k*n^2 \geq n^2 - 3*n + 10 \quad \text{for all } n \geq n_0 .$$

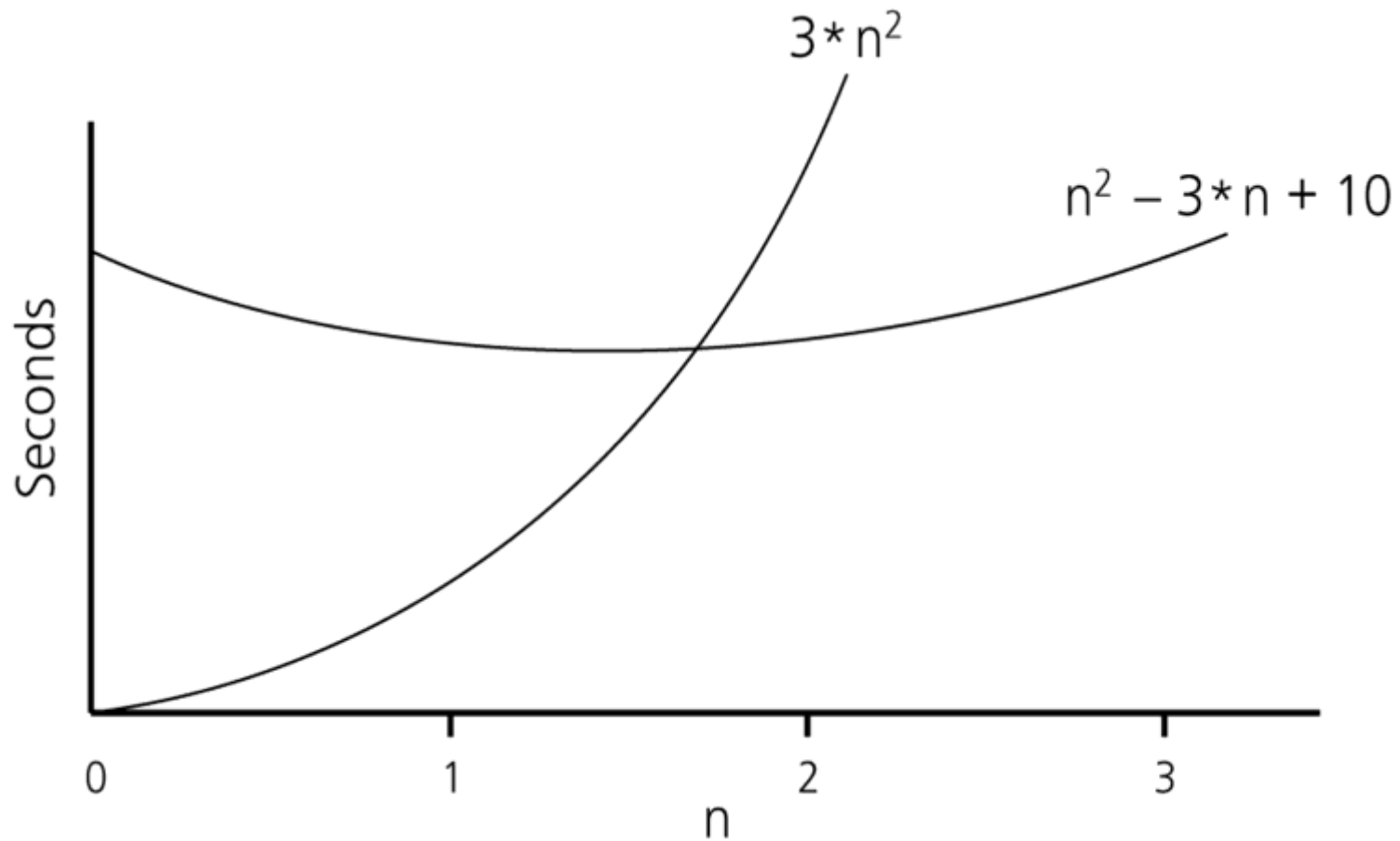
the algorithm is order n^2 (In fact, k is 3 and n_0 is 2)

$$3*n^2 \geq n^2 - 3*n + 10 \text{ for all } n \geq 2 .$$

Thus, the algorithm requires no more than $k*n^2$ time units for $n \geq n_0$,

So it is $O(n^2)$

Order of an Algorithm



Order of an Algorithm

- **Show $2^x + 17$ is $O(2^x)$**
- **$2^x + 17 \leq 2^x + 2^x = 2 \cdot 2^x$ for $x > 5$**
- **Hence $k = 2$ and $n_0 = 5$**

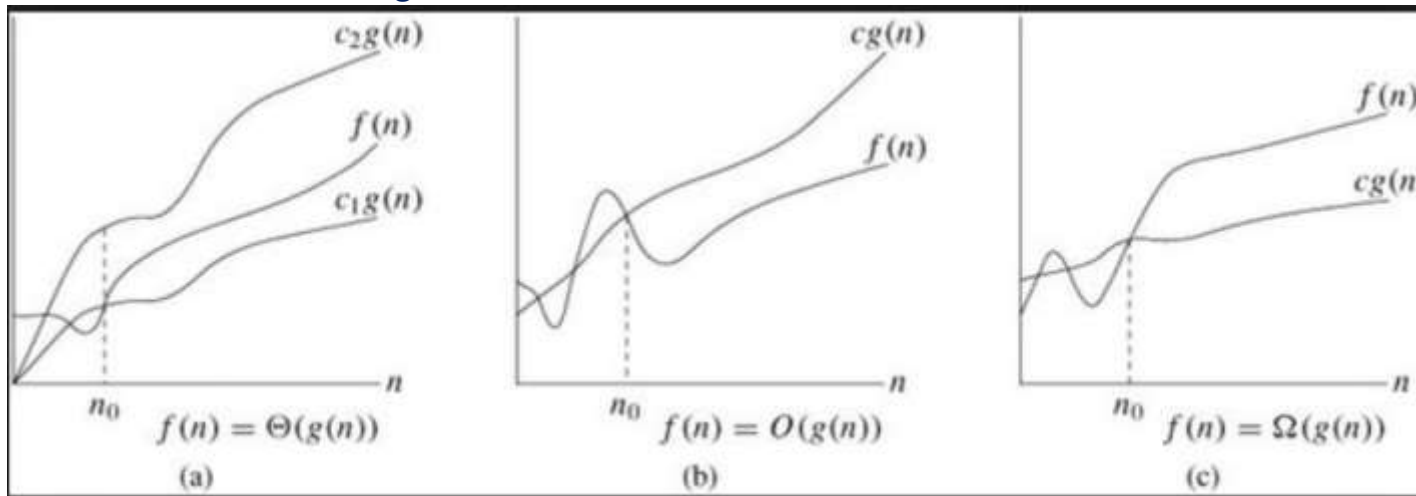
Order of an Algorithm

- Show $2^x + 17$ is $O(3^x)$
- $2^x + 17 \leq k3^x$
- Easy to see that rhs grows faster than lhs over time $\rightarrow k=1$
- However when x is small 17 will still dominate \rightarrow skip over some smaller values of x by using $n_0 = 2$
- Hence $k = 1$ and $n_0 = 2$

Definition of the Order of an Algorithm

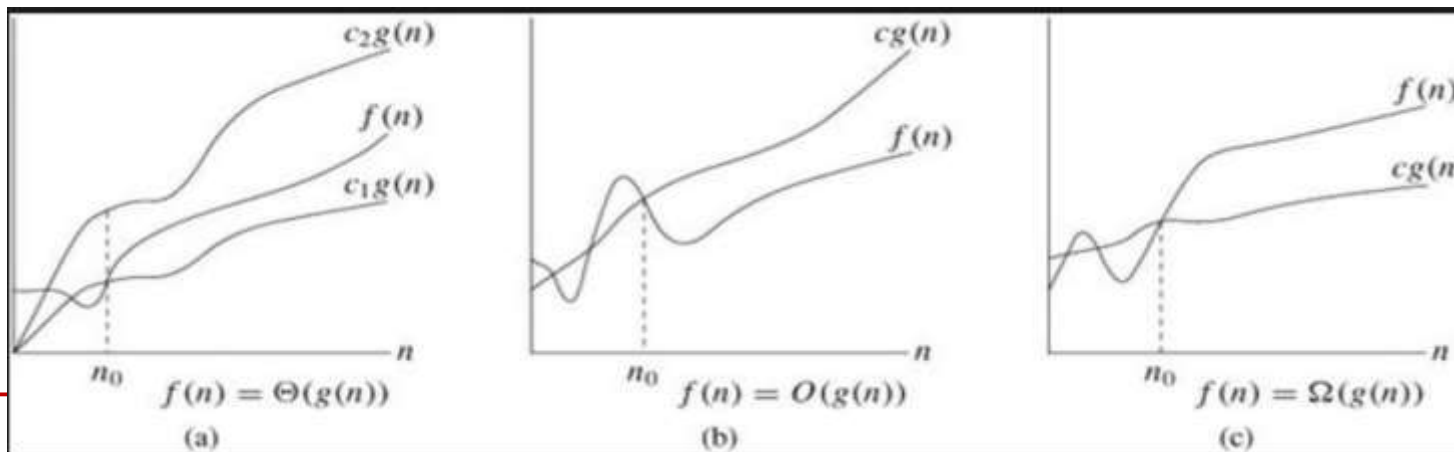
Definition:

Algorithm A is omega $g(n)$ – denoted as $\Omega(g(n))$ – if constants k and n_0 exist such that A requires more than $k * g(n)$ time units to solve a problem of size $n \geq n_0$. $\Rightarrow f(n) \geq k * g(n)$ for all $n \geq n_0$



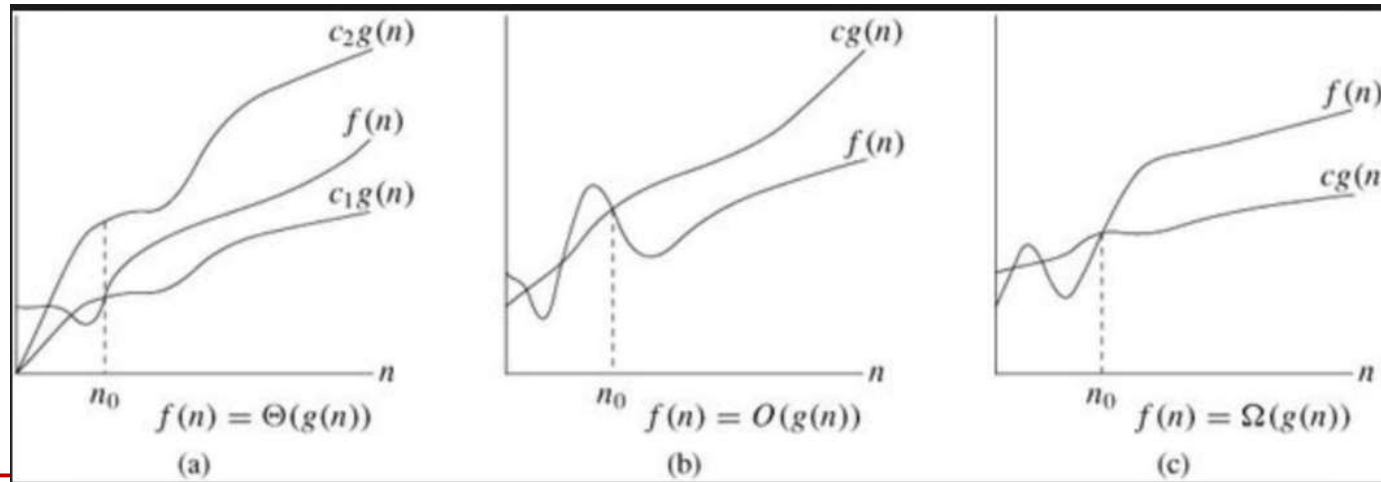
Definition of the Order of an Algorithm

- **Definition:** The function $f(n) = \Theta(g(n))$ if and only if there exist positive constants c_1 , c_2 , n_0 such that $c_1g(n) \leq f(n) \leq c_2g(n)$, $\forall n \geq n_0$. Theta can be used to denote tight bounds of an algorithm. i.e., $g(n)$ is a lower bound as well as an upper bound for $f(n)$.
- Note that $f(n) = \Theta(g(n))$ if and only if $f(n) = \Omega(g(n))$ and $f(n) = O(g(n))$.



Order of an Algorithm

- Show $f(n) = 7n^2 + 1$ is $\Theta(n^2)$
 - You need to show $f(n)$ is $O(n^2)$ and $f(n)$ is $\Omega(n^2)$
 - $f(n)$ is $O(n^2)$ because $7n^2 + 1 \leq 7n^2 + n^2 \forall n \geq 1 \rightarrow k_2 = 8 \ n_0 = 1$
 - $f(n)$ is $\Omega(n^2)$ because $7n^2 + 1 \geq 7n^2 \forall n \geq 0 \rightarrow k_1 = 7 \ n_0 = 0$
 - Pick the largest n_0 to satisfy both conditions naturally $\rightarrow k_1 = 8, k_2 = 7, n_0 = 1$



Growth-Rate Functions

- $O(1)$** Time requirement is constant, and it is independent of the problem's size.
- $O(\log_2 n)$** Time requirement for a logarithmic algorithm increases slowly as the problem size increases.
- $O(n)$** Time requirement for a linear algorithm increases directly with the size of the problem.
- $O(n \cdot \log_2 n)$** Time requirement for a $n \cdot \log_2 n$ algorithm increases more rapidly than a linear algorithm.
- $O(n^2)$** Time requirement for a quadratic algorithm increases rapidly with the size of the problem.
- $O(n^3)$** Time requirement for a cubic algorithm increases more rapidly with the size of the problem than the time requirement for a quadratic algorithm.
- $O(2^n)$** As the size of the problem increases, the time requirement for an exponential algorithm increases too rapidly to be practical.

Properties of Growth-Rate Functions

1. We can ignore low-order terms in an algorithm's growth-rate function.

- If an algorithm is $O(n^3+4n^2+3n)$, it is also $O(n^3)$.
- We only use the higher-order term as algorithm's growth-rate function.

2. We can ignore a multiplicative constant in the higher-order term of an algorithm's growth-rate function.

- If an algorithm is $O(5n^3)$, it is also $O(n^3)$.

3. $O(f(n)) + O(g(n)) = O(f(n)+g(n))$

- We can combine growth-rate functions.
- If an algorithm is $O(n^3) + O(4n)$, it is also $O(n^3+4n^2) \rightarrow$ So, it is $O(n^3)$.
- Similar rules hold for multiplication.

Growth-Rate Functions – Example1

	<u>Cost</u>	<u>Times</u>
<code>i = 1;</code>	<code>c1</code>	<code>1</code>
<code>sum = 0;</code>	<code>c2</code>	<code>1</code>
<code>while (i <= n) {</code>	<code>c3</code>	<code>n+1</code>
<code>i = i + 1;</code>	<code>c4</code>	<code>n</code>
<code>sum = sum + i;</code>	<code>c5</code>	<code>n</code>
<code>}</code>		

$$\begin{aligned}T(n) &= c1 + c2 + (n+1)*c3 + n*c4 + n*c5 \\&= (c3+c4+c5)*n + (c1+c2+c3) \\&= a*n + b\end{aligned}$$

➔ So, the growth-rate function for this algorithm is $O(n)$

Growth-Rate Functions – Example2

	<u>Cost</u>	<u>Times</u>
<code>i=1;</code>	<code>c1</code>	1
<code>sum = 0;</code>	<code>c2</code>	1
<code>while (i <= n) {</code>	<code>c3</code>	$n+1$
<code>j=1;</code>	<code>c4</code>	n
<code>while (j <= n) {</code>	<code>c5</code>	$n*(n+1)$
<code>sum = sum + i;</code>	<code>c6</code>	$n*n$
<code>j = j + 1;</code>	<code>c7</code>	$n*n$
<code>}</code>		
<code>i = i + 1;</code>	<code>c8</code>	n
<code>}</code>		
T(n)	$= c1 + c2 + (n+1)*c3 + n*c4 + n*(n+1)*c5 + n*n*c6 + n*n*c7 + n*c8$	
	$= (c5+c6+c7)*n^2 + (c3+c4+c5+c8)*n + (c1+c2+c3)$	
	$= a*n^2 + b*n + c$	

➔ So, the growth-rate function for this algorithm is $O(n^2)$

Growth-Rate Functions Recursive Algorithms

```
int fact(int n) {  
    if (n == 0)  
        return (1);  
    else  
        return (n * fact(n-1));  
}
```

$$T(n) = T(n-1) + c$$

$$= (T(n-2) + c) + c$$

$$\bullet \quad = (T(n-3) + c) + c + c$$

$$\bullet \quad = (T(n-i) + i*c)$$

$$\bullet \text{ when } i=n \rightarrow T(0) + n*c \rightarrow T(n) = O(n)$$

Sequential Search

```
int sequentialSearch(const int a[], int item, int n){  
    for (int i = 0; i < n && a[i] != item; i++);  
    if (i == n)  
        return -1;  
    return i;  
}
```

Unsuccessful Search: ➔ $O(n)$

Successful Search:

Best-Case: *item* is in the first location of the array ➔ $O(1)$

Worst-Case: *item* is in the last location of the array ➔ $O(n)$

Average-Case: The number of key comparisons 1, 2, ..., n

$$\frac{\sum_{i=1}^n i}{n} = \frac{(n^2 + n)/2}{n} \quad \text{➔ } O(n)$$

Binary Search

We can do binary search if the array is sorted:

```
int binarySearch(int a[], int size, int x) {
    int low = 0;
    int high = size - 1;
    int mid;          // mid will be the index of
                      // target when it's found.
    while (low <= high) {
        mid = (low + high) / 2;
        if (a[mid] < x)
            low = mid + 1;
        else if (a[mid] > x)
            high = mid - 1;
        else
            return mid;
    }
    return -1;
}
```

Binary Search – Analysis

- **For an unsuccessful search:**
 - The number of iterations in the loop is $\lfloor \log_2 n \rfloor + 1$
 → $O(\log_2 n)$
- **For a successful search:**
 - *Best-Case:* The number of iterations is 1. **→ $O(1)$**
 - *Worst-Case:* The number of iterations is $\lfloor \log_2 n \rfloor + 1$ **→ $O(\log_2 n)$**
 - *Average-Case:* The avg. # of iterations $< \log_2 n$ **→ $O(\log_2 n)$**

0 1 2 3 4 5 6 ← an array with size 7

3 2 3 1 3 2 3 ← # of iterations

The average # of iterations = $17/7 = 2.4285 < \log_2 7$

References

- **Data Structure and Algorithms for Electrical Engineering by Yung Yi**
- **CENG707 - Data Structures and Algorithms by Yusuf Sahillioğlu**