

## EC330: Applied Algorithms for Engineers

### Asymptotic Notation

### What is an algorithm?

- An unambiguous list of steps (program) to transform some input into some output
- Pick a Problem (set)
- Find method to solve
  1. Correct for all cases (elements of set)
  2. Each step is finite ( $\Delta t_{\text{step}} < \text{max time}$ )
  3. Next step is unambiguous
  4. Terminate in finite number of steps

## What is an Algorithm?

```

Selection Sort(A[1...n])
for (i=1 to n)
  for j=i+1 to n
    if A[i]>A[j] then
      swap A[i] and A[j]
    
```

**Lemma:** After iteration  $j$  of the inner loop  
 $A[i]$  is the smallest element of  $A[i...j]$ .

“loop invariant”

**Theorem:** Selection Sort puts the elements of  
 $A[]$  into increasing order.

Proof by induction.

## How fast is Selection Sort?

```

Selection Sort(A[1...n])
for (i=1 to n)
  for j=i+1 to n
    if A[i]>A[j] then
      swap A[i] and A[j]
    
```

$$\left. \left. \left. \right\} 2 \right\} \sum_{j=i+1}^n 2 \right\} \sum_{i=1}^n \sum_{j=i+1}^n 2$$

It depends!

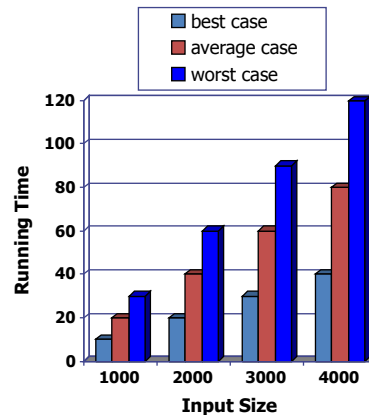
- What computer? What language? What compiler?  
 What operating system? What architecture?
- How long does it take to compare  $A[i]$  and  $A[j]$ ?  
 ...to swap  $A[i]$  and  $A[j]$ ? To find  $A[i]$ ?
- If swap and comparison take 1 unit of time, how much  
 time do they take?

$$\sum_{i=1}^n \sum_{j=i+1}^n 2$$

- How does this compare to  $n^3$ ,  $n^2$ ,  $n^3/100$ ?

## Running Time

- Most algorithms transform input objects into output objects
- The running time of an algorithm typically grows with the input size
- Average case time is often difficult to determine
- We often focus on the worst case running time
  - Easier to analyze
  - Crucial to applications such as games, finance and robotics

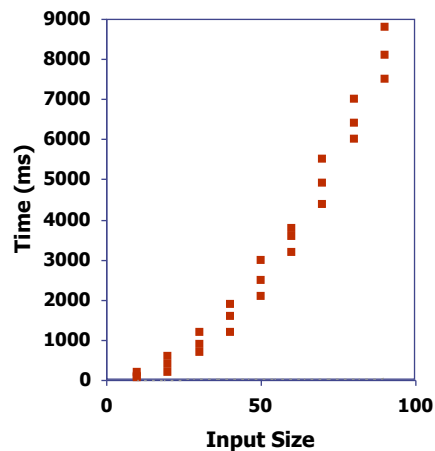


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## Experimental Studies

- Write a program to implementing the algorithm
- Run the program with inputs of varying size and composition
- Use a method like `clock()` to get an accurate measure of the actual running time
- Plot the results



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## Limitations of Experiments

- It is necessary to implement the algorithm, which may be difficult
- Results may not be indicative of the running time on other inputs not included in the experiment
- In order to compare two algorithms, the same hardware and software environments must be used



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## Theoretical Analysis



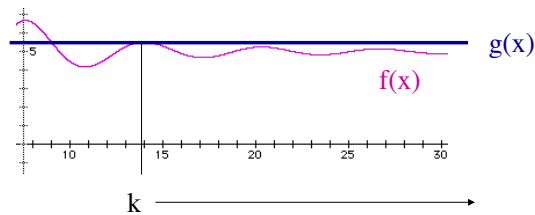
- Uses a **high-level description** of the algorithm instead of an implementation
- Characterizes running time as a function of the input size,  $n$
- Takes into account **all possible inputs**
- Allows us to evaluate the speed of an algorithm independent of the hardware/software environment

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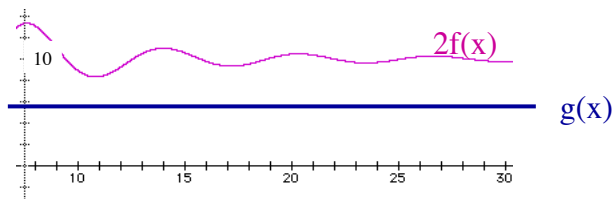
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## The Land of O()

- Which function is “bigger”?
  - Only **care about eventual size** (asymptotic)



- Don't care about multiplicative constants



## The Land of O()

**Big-O:** for functions that map real numbers (or a subset) to real numbers (or a subset)

**Intuitively:**  $f(n)$  is  $O(g(n))$  if  $f$  is eventually smaller or equal to  $g$  or some multiple of  $g$

**“Real” Definition:**  $f(n)$  is  $O(g(n))$  iff  
 $\exists c > 0 \quad \exists n_0 > 0 \quad |f(n)| \leq c|g(n)|$  whenever  $n > n_0$ .

**“Math-freak” Definition:**  $f(n)$  is  $O(g(n))$  if  
 $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)}$  is finite.

## O() Examples

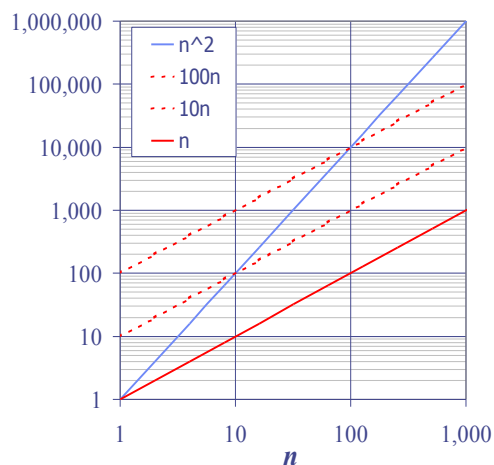
**“Real” Definition:**  $f(n)$  is  $O(g(n))$  iff  
 $\exists c > 0 \ \exists n_0 > 0 \ |f(n)| \leq c|g(n)|$  whenever  $n > n_0$ .

	$c$	$n_0$
$n$ is $O(n)$	1	1
$n$ is $O(5n)$	1	1
$n$ is $O(n/2-17)$	100	1
$n$ is $O(n/10^{100})$	$10^{100}$	1
$5n+3$ is $O(n^2)$	25	6 [proof by induction]

$n^2$  is not  $O(5n+3)$

## Big-Oh Example

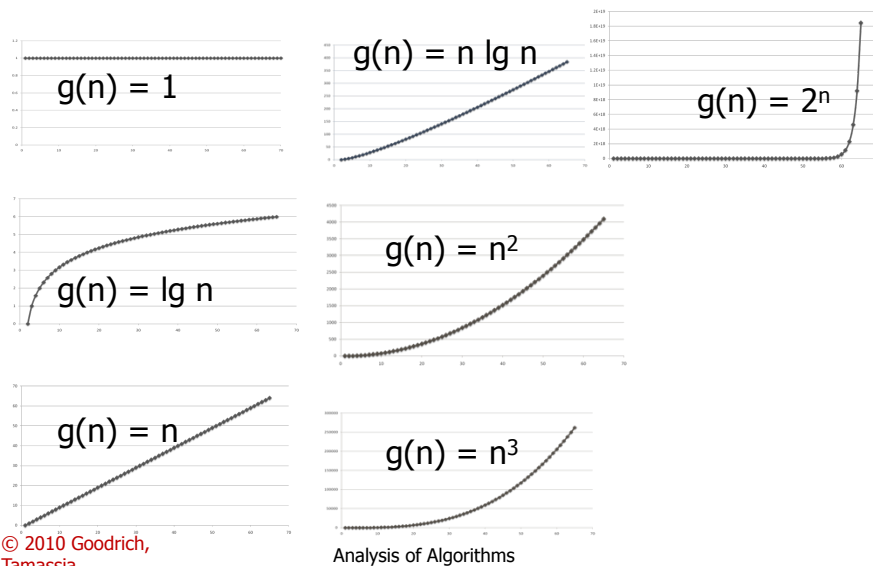
- Example: the function  $n^2$  is not  $O(n)$ 
  - $n^2 \leq cn$
  - $n \leq c$
  - The above inequality cannot be satisfied since  $c$  must be a constant



## Why is big-O Important?

input size	(machine does 1,000,000 steps per second)					
time	10	20	30	40	50	60
$\log n$	3.3μsec	4.4μsec	5μsec	5.3μsec	5.6μsec	5.9μsec
$n$	10μsec	20μsec	30μsec	40μsec	50μsec	60μsec
$n^2$	100μsec	400μsec	900μsec	1.5msec	2.5msec	3.6msec
$n^5$	0.1sec	3.2sec	24.3sec	1.7min	5.2min	13min
$3^n$	59msec	48min	6.5yrs	385,500yrs	$2 \times 10^8$ centuries...	
$n!$	3sec	$7.8 \times 10^8$ millenia				

## Functions Graphed



## Big-Oh and Growth Rate

- The big-Oh notation gives an upper bound on the growth rate of a function
- The statement “ $f(n)$  is  $O(g(n))$ ” means that the growth rate of  $f(n)$  is no more than the growth rate of  $g(n)$
- We can use the big-Oh notation to rank functions according to their growth rate

	$f(n)$ is $O(g(n))$	$g(n)$ is $O(f(n))$
$g(n)$ grows more	Yes	No
$f(n)$ grows more	No	Yes
Same growth	Yes	Yes

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## Properties of big-O

**If**  $f_1(n)$  is  $O(g_1(n))$  and  $f_2(n)$  is  $O(g_2(n))$  **then**

- $f_1(n) + f_2(n)$  is  $O(g_1(n) + g_2(n))$
- $f_1(n) + f_2(n)$  is  $O(\max\{g_1(n), g_2(n)\})$
- $f_1(n) * f_2(n)$  is  $O(g_1(n) * g_2(n))$

[prove these to yourself!]

**If**  $f(n)$  is  $O(g(n))$  and  $g(n)$  is  $O(h(n))$  **then**

$f(n)$  is  $O(h(n))$

- Examples:



## Cousins of O()

**$f(n)$  is  $O(g(n))$**  [ “big oh” ] iff

$\exists C > 0 \exists n_0 \quad |f(n)| \leq C|g(n)| \text{ whenever } n > n_0.$

Like

$\leq$

**$f(n)$  is  $\Omega(g(n))$**  [ “big Omega” ] iff

$\exists C > 0 \exists n_0 \quad |f(n)| \geq C|g(n)| \text{ whenever } n > n_0.$

$\Leftrightarrow g(n)$  is  $O(f(n))$

$\geq$

**$f(n)$  is  $\Theta(g(n))$**  [ “big Theta” ] iff

$f(n)$  is  $O(g(n))$  and  $g(n)$  is  $O(f(n))$

$=$

**$f(n)$  is  $o(g(n))$**  [ “little oh” ] iff

$\forall C > 0 \exists n_0 \quad |f(n)| < C|g(n)| \text{ whenever } n > n_0.$

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

*intuitively:*  $f(n)$  is  $O(g(n))$  but  $f(n)$  is **not**  $\Theta(g(n))$

$<$

**$f(n)$  is  $\omega(g(n))$**  [ “little omega” - not doubleyou ] iff

$g(n)$  is  $o(f(n))$

$\Leftrightarrow \lim_{n \rightarrow \infty} f(n)/g(n) = \infty$

$>$

## Rules of Thumb

- For polynomials, only the largest term matters.  
 $a_k x^k + a_{k-1} x^{k-1} + \dots + a_0$  is  $\Theta(x^k)$
- $\log n$  is  $o(n)$   
Proof:  $\lim_{n \rightarrow \infty} \log(n)/n = 0$
- Some common functions in “non-decreasing” order:  
 $1 \quad \log(n) \quad \sqrt{n} \quad n \quad n \log(n) \quad n^2 \quad n^3 \quad n^{100} \quad 2^n \quad 3^n \quad n!$
- Selection sort requires  $\Theta(n^2)$  time.



**“Math-freak” Definition:**  $f(n)$  is  $O(g(n))$  if

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \text{ is finite}$$

$f(n)$  is  $O(g(n))$  [ “big oh” ] iff

$$\exists C > 0 \quad \exists n_0 \quad |f(n)| \leq C|g(n)| \quad \text{whenever } n > n_0.$$

Like

$\leq$

$f(n)$  is  $\Omega(g(n))$  [ “big Omega” ] iff

$$\exists C > 0 \quad \exists n_0 \quad |f(n)| \geq C|g(n)| \quad \text{whenever } n > n_0.$$

$\geq$

$$\Leftrightarrow g(n) \text{ is } O(f(n))$$

$f(n)$  is  $\Theta(g(n))$  [ “big Theta” ] iff

$$f(n) \text{ is } O(g(n)) \text{ and } g(n) \text{ is } O(f(n))$$

$=$

$f(n)$  is  $o(g(n))$  [ “little oh” ] iff

$$\forall C > 0 \quad \exists n_0 \quad |f(n)| < C|g(n)| \quad \text{whenever } n > n_0.$$

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*intuitively:*  $f(n)$  is  $O(g(n))$  but  $f(n)$  is **not**  $\Theta(g(n))$

$f(n)$  is  $\omega(g(n))$  [ “little omega” - not doubleyou ] iff

$$g(n) \text{ is } o(f(n))$$

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$>$