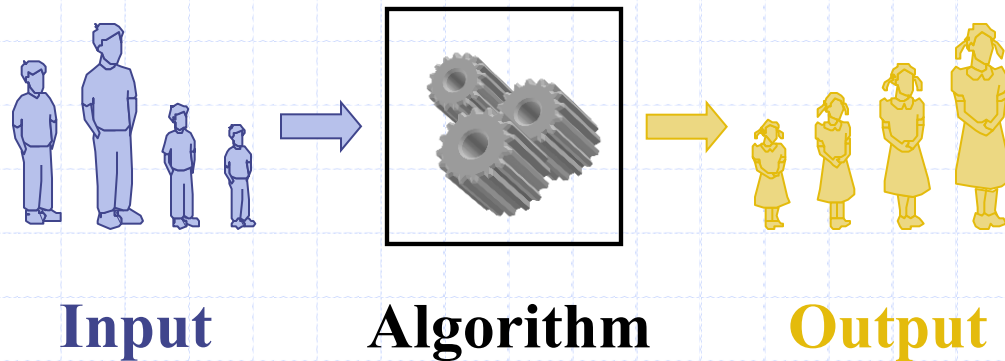


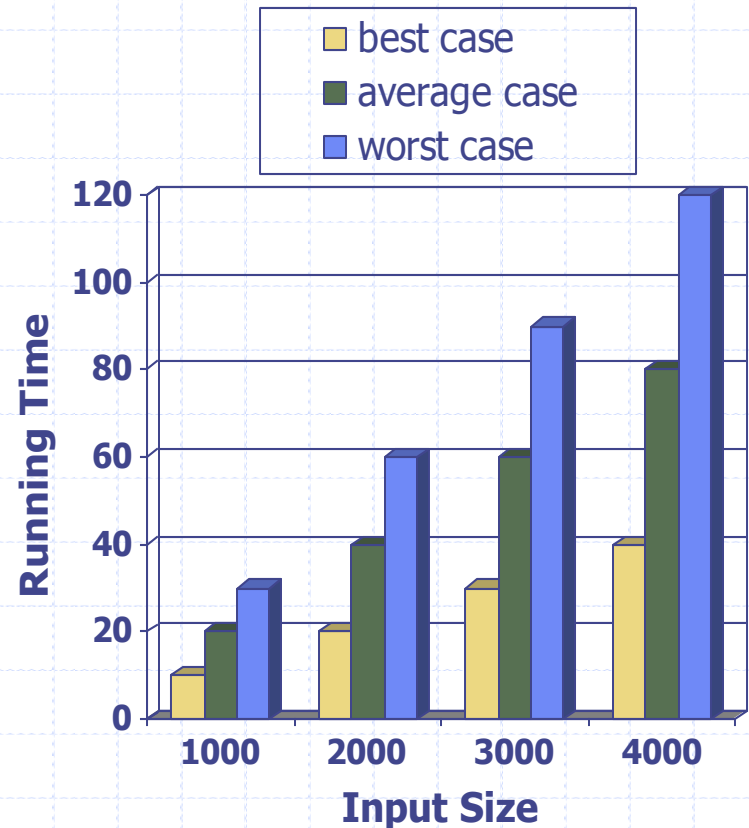
# Analysis of Algorithms



An **algorithm** is a step-by-step procedure for solving a problem in a finite amount of time.

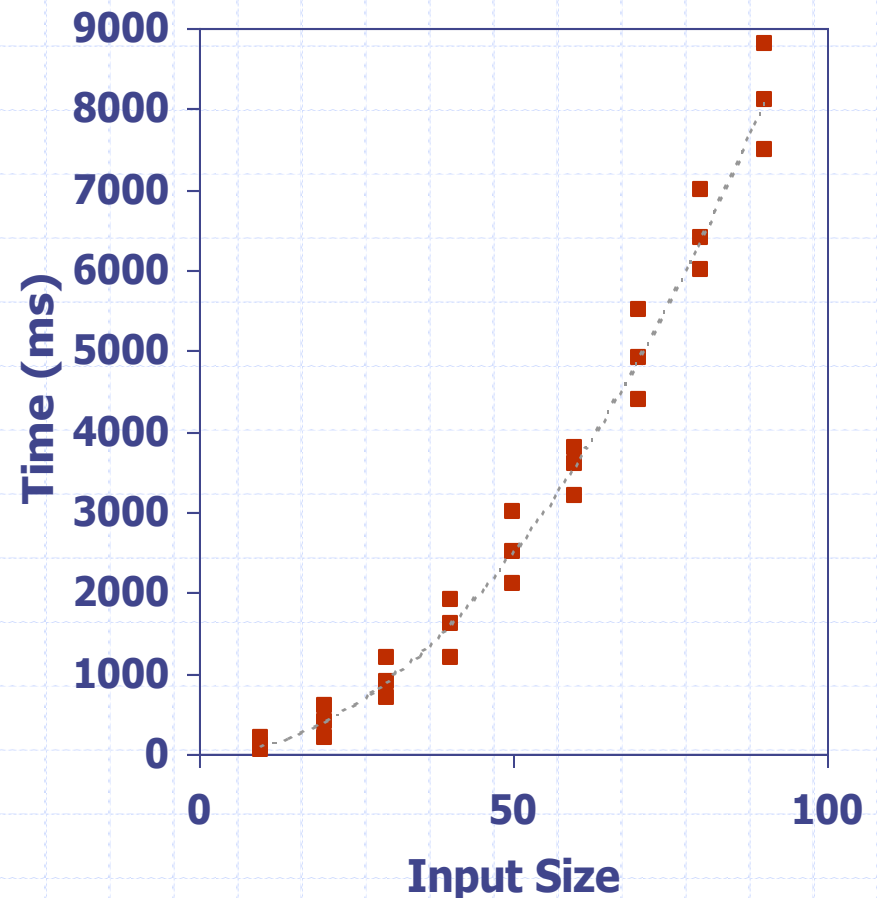
# Running Time

- ◆ 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 focus on the worst case running time.
  - Easier to analyze
  - Crucial to applications such as games, finance and robotics



# Experimental Studies

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



# 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



# 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

# Pseudocode

- ◆ High-level description of an algorithm
- ◆ More structured than English prose
- ◆ Less detailed than a program
- ◆ Preferred notation for describing algorithms
- ◆ Hides program design issues

Example: find max element of an array

**Algorithm** *arrayMax*(*A*, *n*)

**Input** array *A* of *n* integers

**Output** maximum element of *A*

*currentMax*  $\leftarrow A[0]$

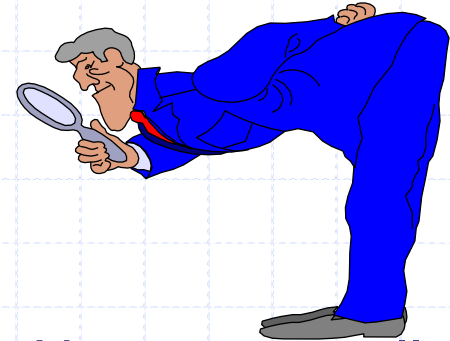
**for** *i*  $\leftarrow 1$  **to** *n* - 1 **do**

**if** *A*[*i*] > *currentMax* **then**

*currentMax*  $\leftarrow A[i]$

**return** *currentMax*

# Pseudocode Details



## ◆ Control flow

- **if ... then ... [else ...]**
- **while ... do ...**
- **repeat ... until ...**
- **for ... do ...**
- Indentation replaces braces

## ◆ Method declaration

**Algorithm** *method* (*arg* [, *arg*...])

**Input** ...

**Output** ...

## ◆ Method/Function call

*var.method* (*arg* [, *arg*...])

## ◆ Return value

**return** *expression*

## ◆ Expressions

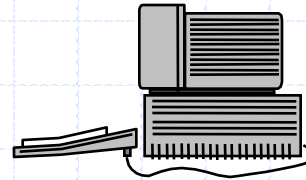
← Assignment  
(like = in C++)

= Equality testing  
(like == in C++)

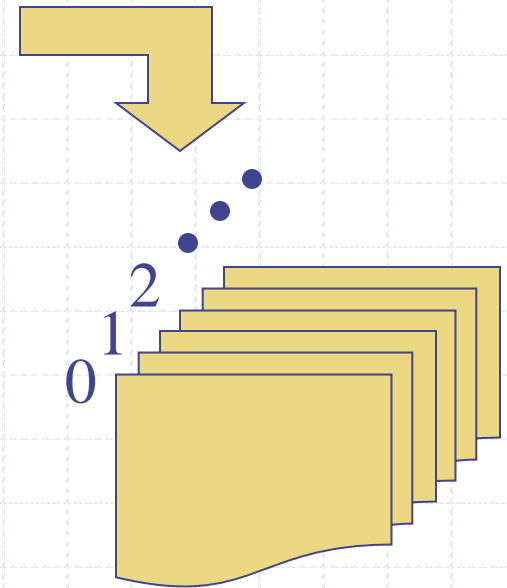
*n*<sup>2</sup> Superscripts and other  
mathematical  
formatting allowed

# The Random Access Machine (RAM) Model

- ◆ A CPU



- ◆ An potentially unbounded bank of **memory** cells, each of which can hold an arbitrary number or character



- ◆ Memory cells are numbered and accessing any cell in memory takes unit time.



# Primitive Operations



- ◆ Basic computations performed by an algorithm
- ◆ Identifiable in pseudocode
- ◆ Largely independent from the programming language
- ◆ Exact definition not important (we will see why later)
- ◆ Assumed to take a constant amount of time in the RAM model

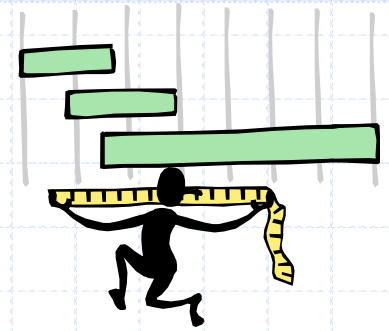
- ◆ Examples:
  - Evaluating an expression
  - Assigning a value to a variable
  - Indexing into an array
  - Calling a method
  - Returning from a method

# Counting Primitive Operations

- ◆ By inspecting the pseudocode, we can determine the maximum number of primitive operations executed by an algorithm, as a function of the input size

Algorithm <i>arrayMax</i> ( <i>A</i> , <i>n</i> )	# operations
<i>currentMax</i> $\leftarrow A[0]$	2
for <i>i</i> $\leftarrow 1$ to <i>n</i> - 1 do	$2 + n$
if <i>A</i> [ <i>i</i> ] > <i>currentMax</i> then	$2(n - 1)$
<i>currentMax</i> $\leftarrow A[i]$	$2(n - 1)$
{ increment counter <i>i</i> }	$2(n - 1)$
return <i>currentMax</i>	1
Total	$7n - 1$

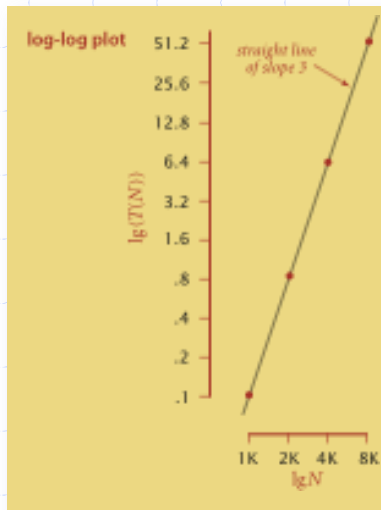
# Estimating Running Time



- ◆ Algorithm *arrayMax* executes  $7n - 1$  primitive operations in the worst case.
- ◆ Define:
  - $a$  = Time taken by the fastest primitive operation
  - $b$  = Time taken by the slowest primitive operation
- ◆ Let  $T(n)$  be worst-case time of *arrayMax*. Then
$$a(7n - 1) \leq T(n) \leq b(7n - 1)$$
- ◆ Hence, the running time  $T(n)$  is bounded by two linear functions

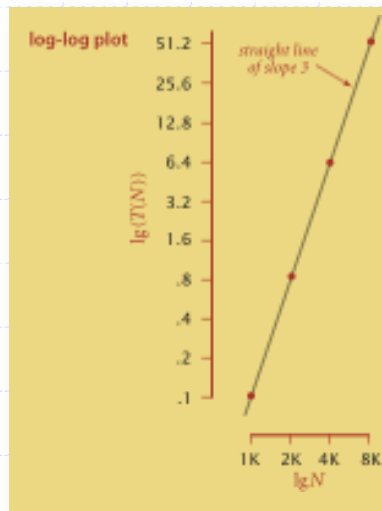
# Power Law

◆ Log-log plot. Plot running time  $T(N)$  vs. input size  $N$  using log-log scale.



# Power Law

- ◆ Log-log plot. Plot running time  $T(N)$  vs. input size  $N$  using log-log scale.



Let  $T(N) = a N^b$ , where  $a = 2^c$

Thus  $\lg(T(N)) = b \lg N + c$

After regression:

$b = 2.999$

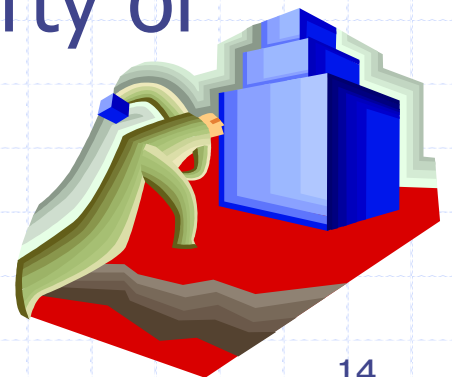
$c = -33.2103$

power law

- ◆ Regression. Fit straight line through data points:  $a N^b$ .
- ◆ Hypothesis. The running time is about  $1.006 \times 10^{-10} \times N^{2.999}$  seconds.

# Growth Rate of Running Time

- ◆ Changing the hardware/ software environment
  - Affects  $T(n)$  by a constant factor
  - But does not alter the growth rate of  $T(n)$
- ◆ The linear growth rate of the running time  $T(n)$  is an intrinsic property of algorithm *arrayMax*

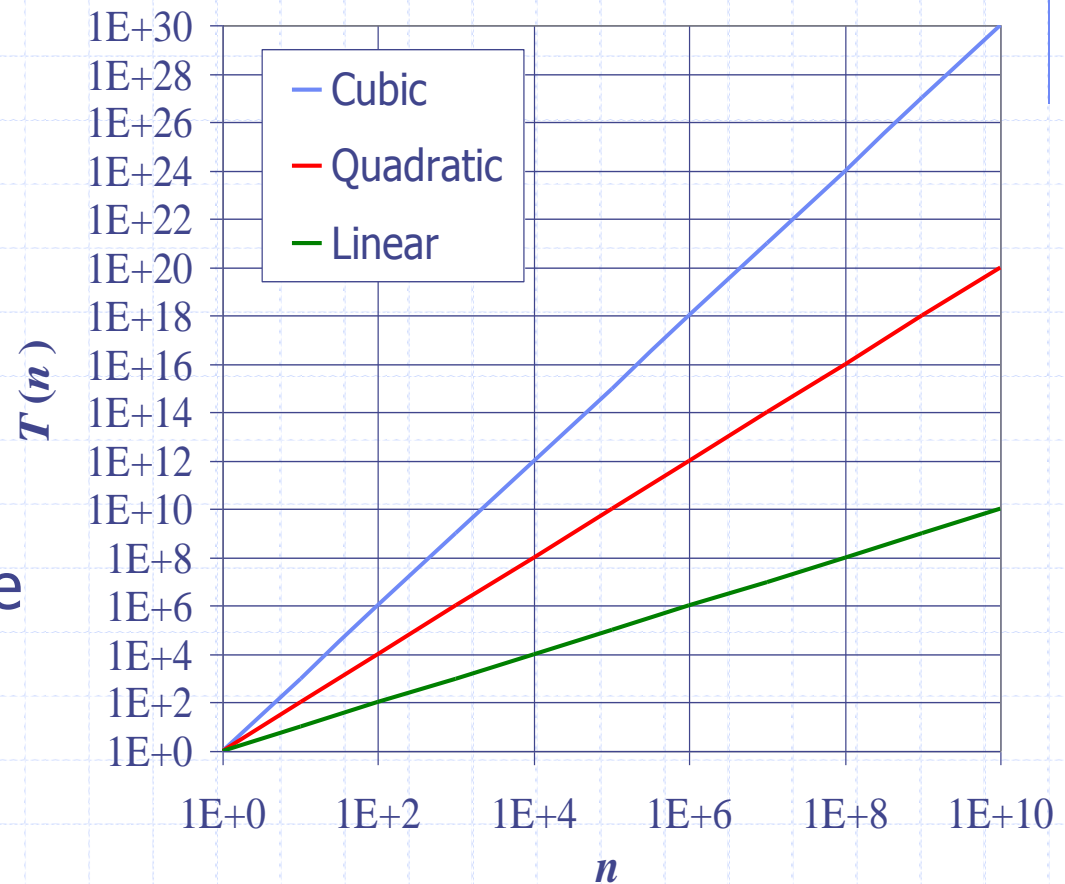


# Growth Rates

## ◆ Growth rates of functions:

- Linear  $\approx n$
- Quadratic  $\approx n^2$
- Cubic  $\approx n^3$

## ◆ In a log-log chart, the slope of the line corresponds to the growth rate of the function



# Practical implications of order-of-growth

growth rate	problem size solvable in minutes			
	1970s	1980s	1990s	2000s
1	any	any	any	any
$\log N$	any	any	any	any
$N$	millions	tens of millions	hundreds of millions	billions
$N \log N$	hundreds of thousands	millions	millions	hundreds of millions
$N^2$	hundreds	thousand	thousands	tens of thousands
$N^3$	hundred	hundreds	thousand	thousands
$2^N$				



# Practical implications of order-of-growth

growth rate	problem size solvable in minutes			
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$N \log N$	hundreds of thousands	millions	millions	hundreds of millions
$N^2$	hundreds	thousand	thousands	tens of thousands
$N^3$	hundred	hundreds	thousand	thousands
$2^N$	20	20s	20s	30

# Practical implications of order-of-growth

growth rate	name	description	effect on a program that runs for a few seconds	
			time for 100x more data	size for 100x faster computer
1	constant	independent of input size	–	–
$\log N$	logarithmic	nearly independent of input size	–	–
$N$	linear	optimal for $N$ inputs	a few minutes	100x
$N \log N$	linearithmic	nearly optimal for $N$ inputs	a few minutes	100x
$N^2$	quadratic	not practical for large problems	several hours	10x
$N^3$	cubic	not practical for medium problems	several weeks	4–5x
$2^N$	exponential			

# Practical implications of order-of-growth

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$N$	linear	optimal for $N$ inputs	a few minutes	100x
$N \log N$	linearithmic	nearly optimal for $N$ inputs	a few minutes	100x
$N^2$	quadratic	not practical for large problems	several hours	10x
$N^3$	cubic	not practical for medium problems	several weeks	4–5x
$2^N$	exponential	useful only for tiny problems	forever	1x

# Practical implications of order-of-growth

growth rate	problem size solvable in minutes				time to process millions of inputs			
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s
1	any	any	any	any	instant	instant	instant	instant
log N	any	any	any	any	instant	instant	instant	instant
N	millions	tens of millions	hundreds of millions	billions	minutes	seconds	second	instant
N log N	hundreds of thousands	millions	millions	hundreds of millions	hour	minutes	tens of seconds	seconds
N <sup>2</sup>	hundreds	thousand	thousands	tens of thousands	decades	years	months	weeks
N <sup>3</sup>								

# Practical implications of order-of-growth

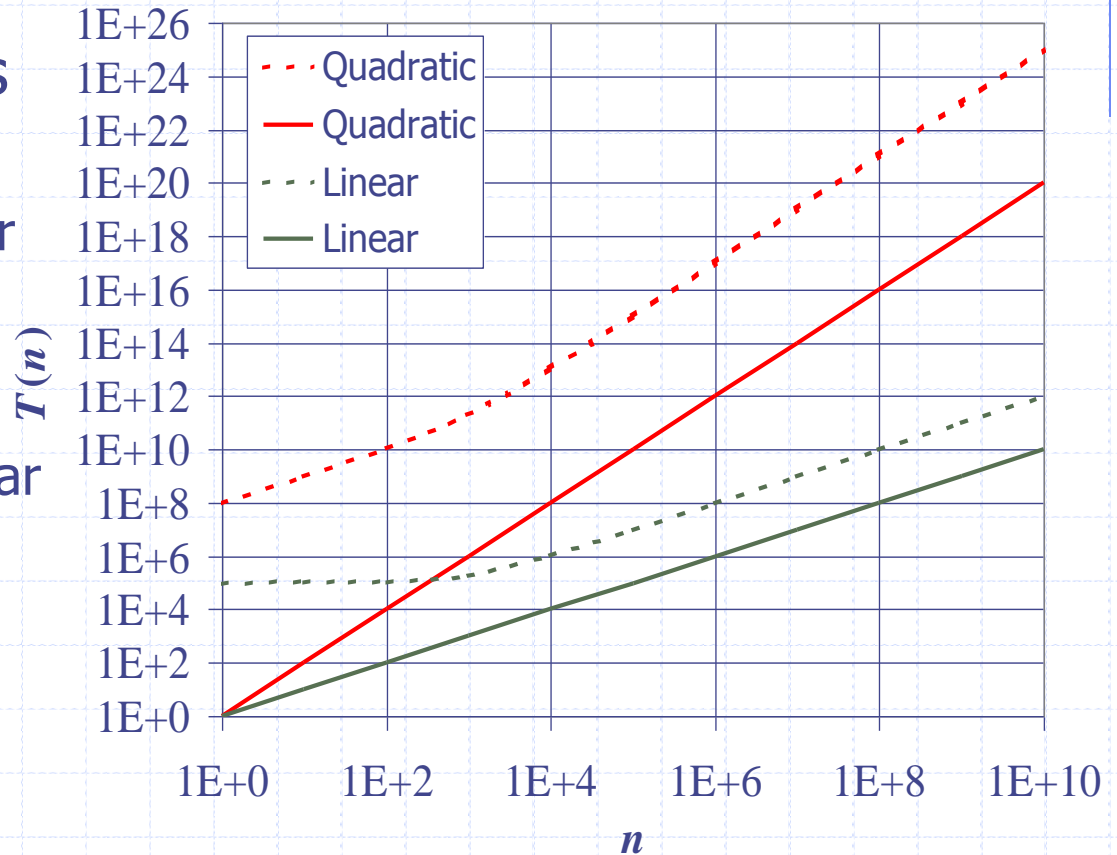
growth rate	problem size solvable in minutes				time to process millions of inputs			
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s
1	any	any	any	any	instant	instant	instant	instant
log N	any	any	any	any	instant	instant	instant	instant
N	millions	tens of millions	hundreds of millions	billions	minutes	seconds	second	instant
N log N	hundreds of thousands	millions	millions	hundreds of millions	hour	minutes	tens of seconds	seconds
N <sup>2</sup>	hundreds	thousand	thousands	tens of thousands	decades	years	months	weeks
N <sup>3</sup>	hundred	hundreds	thousand	thousands				

# Practical implications of order-of-growth

growth rate	problem size solvable in minutes				time to process millions of inputs			
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s
1	any	any	any	any	instant	instant	instant	instant
log N	any	any	any	any	instant	instant	instant	instant
N	millions	tens of millions	hundreds of millions	billions	minutes	seconds	second	instant
N log N	hundreds of thousands	millions	millions	hundreds of millions	hour	minutes	tens of seconds	seconds
N <sup>2</sup>	hundreds	thousand	thousands	tens of thousands	decades	years	months	weeks
N <sup>3</sup>	hundred	hundreds	thousand	thousands	never	never	never	millennia

# Constant Factors

- ◆ The growth rate is not affected by
  - constant factors or
  - lower-order terms
- ◆ Examples
  - $10^2n + 10^5$  is a linear function
  - $10^5n^2 + 10^8n$  is a quadratic function



# Big-Oh Notation

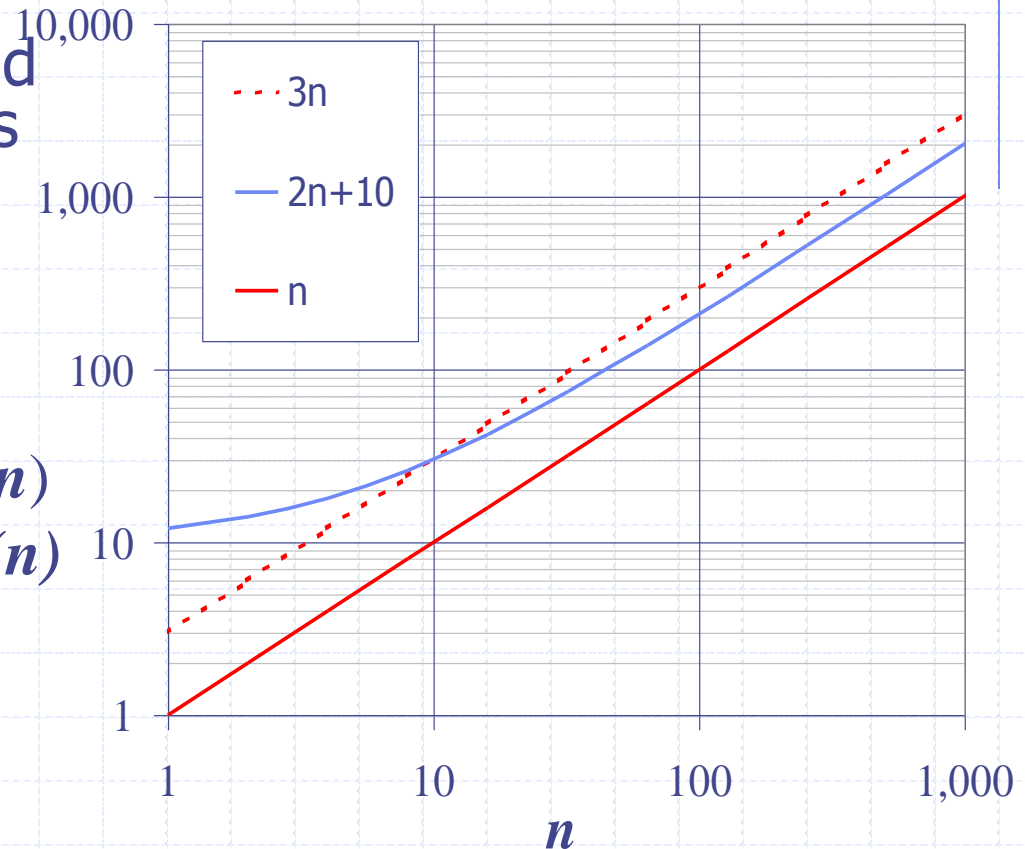
◆ Given functions  $f(n)$  and  $g(n)$ , we say that  $f(n)$  is  $O(g(n))$  if there are positive constants  $c$  and  $n_0$  such that

$$f(n) \leq cg(n) \text{ for } n \geq n_0$$

◆ Example:  $2n + 10$  is  $O(n)$

◆ For what  $c$  and  $n$  is  $cn \geq f(n)$ ?

- $2n + 10 \leq cn$
- $(c - 2)n \geq 10$
- $n \geq 10/(c - 2)$
- Pick  $c = 3$  and  $n_0 = 10$

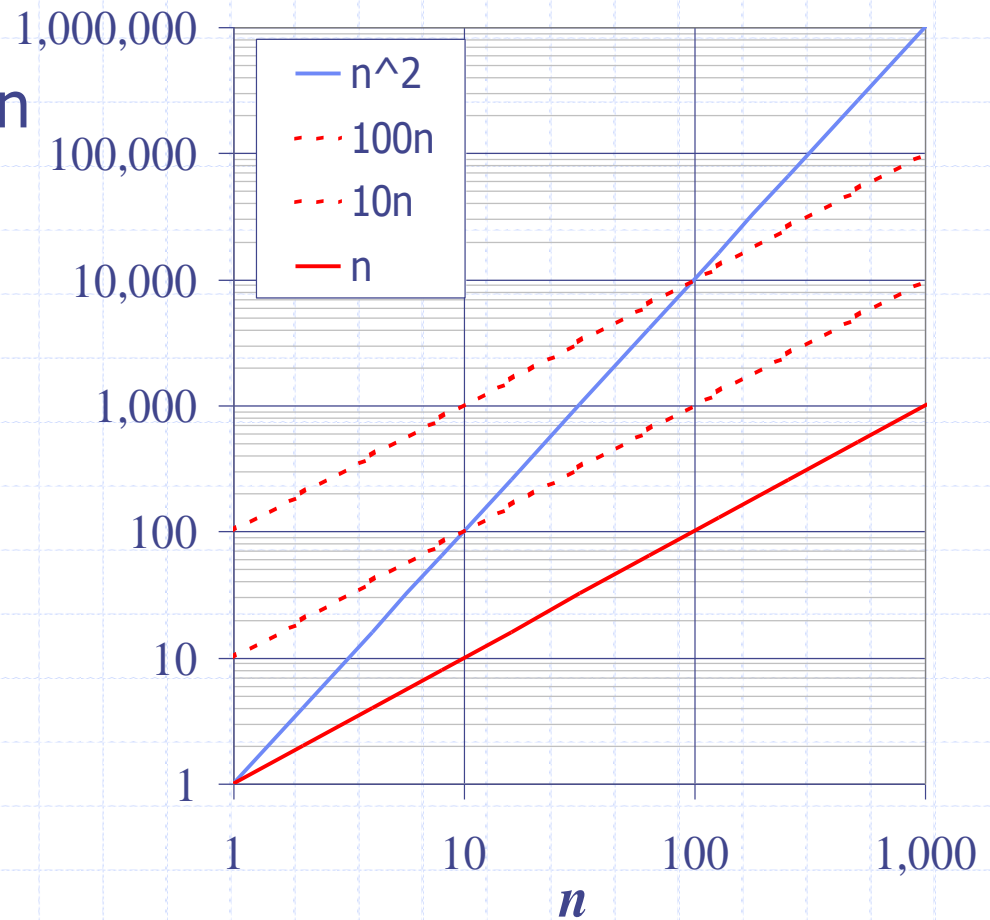




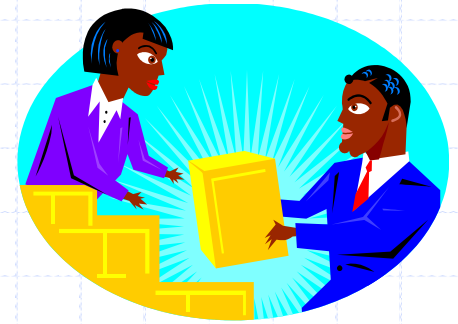
# Big-Oh Example

◆ 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



# More Big-Oh Examples



◆  $7n-2$

e.g. Is there a  $c$  and  $n_0$  such that  $c \bullet n \geq 7n-2$ ?

What is the big-Oh?

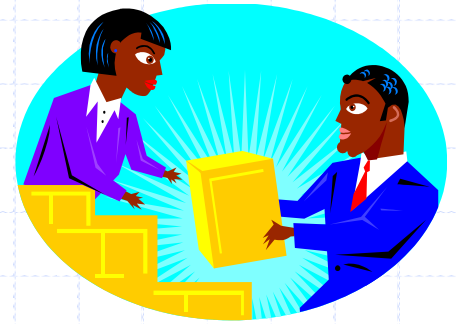
$7n-2$  is  **$O(n)$**

[TEAMS] What are the values for  $c$  and  $n_0$  ?

Need  $c > 0$  and  $n_0 \geq 1$  such that  $7n-2 \leq c \bullet n$  for  $n \geq n_0$

This is true for  $c = 7$  and  $n_0 = 1$

# More Big-Oh Examples



## ■ $2n^2 + 16$

$2n^2 + 16$  is  **$O(n^2)$**

need  $c > 0$  and  $n_0 \geq 1$  such that  $2n^2 + 16 \leq c \cdot n^2$  for  $n \geq n_0$

this is true for  $c = 3$  and  $n_0 = 4$

## ■ $3n^3 + 2n^2 + 9$

$3n^3 + 2n^2 + 9$  is  **$O(n^3)$**

need  $c > 0$  and  $n_0 \geq 1$  such that  $3n^3 + 2n^2 + 9 \leq c \cdot n^3$  for  $n \geq n_0$

this is true for  $c = 4$  and  $n_0 = 3$

# 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

# Big-Oh Rules



- ◆ If  $f(n)$  is a polynomial of degree  $d$ , then  $f(n)$  is  $O(n^d)$ , i.e.,
  1. Drop lower-order terms
  2. Drop constant factors
- ◆ Use the smallest possible class of functions
  - Say " $2n$  is  $O(n)$ " instead of " $2n$  is  $O(n^2)$ "
- ◆ Use the simplest expression of the class
  - Say " $3n + 5$  is  $O(n)$ " instead of " $3n + 5$  is  $O(3n)$ "

# Asymptotic Algorithm Analysis

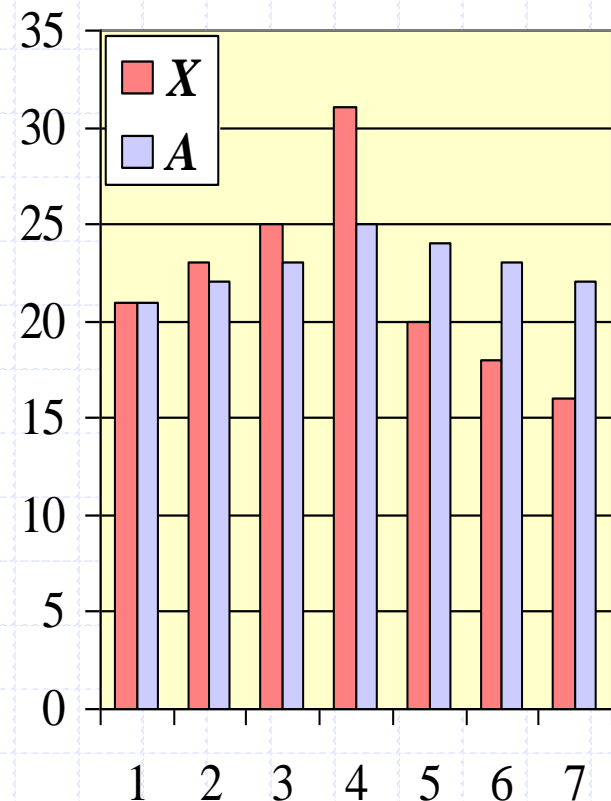
- ◆ The asymptotic analysis of an algorithm determines the running time in big-Oh notation
- ◆ To perform the asymptotic analysis
  - We find the worst-case number of primitive operations executed as a function of the input size
  - We express this function with big-Oh notation
- ◆ Example:
  - We determine that algorithm *arrayMax* executes at most  $7n - 1$  primitive operations
  - We say that algorithm *arrayMax* “runs in  $O(n)$  time”
- ◆ Since constant factors and lower-order terms are eventually dropped anyhow, we can disregard them when counting primitive operations

# Computing Prefix Averages

- ◆ We further illustrate asymptotic analysis with two algorithms for prefix averages
- ◆ The  $i$ -th prefix average of an array  $X$  is average of the first  $(i + 1)$  elements of  $X$ :

$$A[i] = (X[0] + X[1] + \dots + X[i]) / (i+1)$$

- ◆ Computing the array  $A$  of prefix averages of another array  $X$  has applications to financial analysis



# Prefix Averages (Quadratic)

- ◆ The following algorithm computes prefix averages in quadratic time by applying the definition

**Algorithm** *prefixAverages1*( $X, n$ )

**Input** array  $X$  of  $n$  integers

**Output** array  $A$  of prefix averages of  $X$       #operations

$A \leftarrow$  new array of  $n$  integers       $n$

**for**  $i \leftarrow 0$  **to**  $n - 1$  **do**       $n$

$s \leftarrow X[0]$        $n$

**for**  $j \leftarrow 1$  **to**  $i$  **do**       $1 + 2 + \dots + (n - 1)$

$s \leftarrow s + X[j]$        $1 + 2 + \dots + (n - 1)$

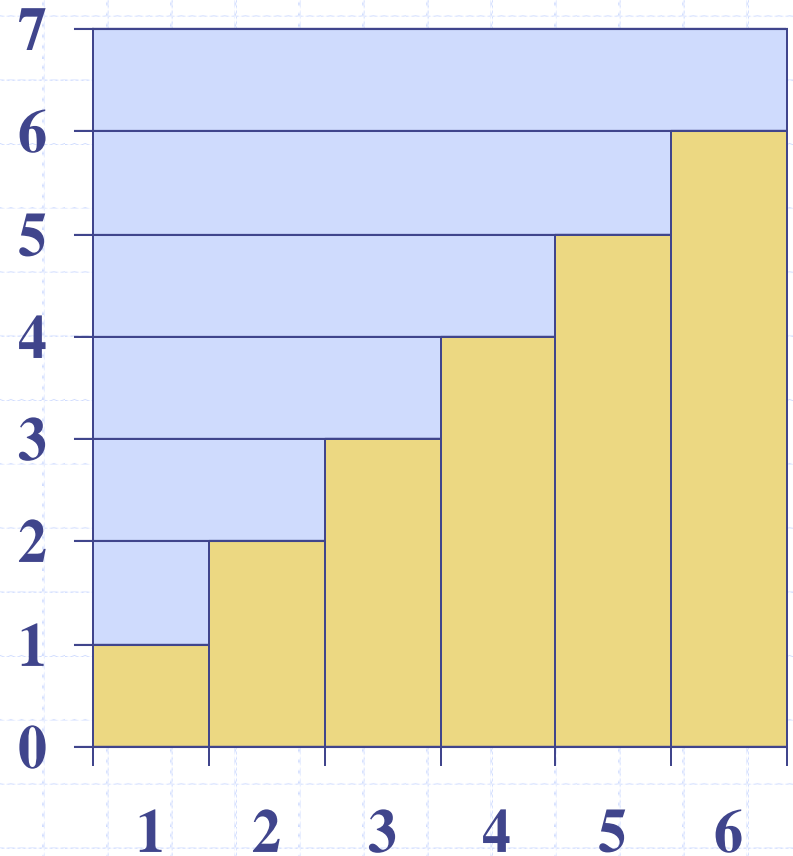
$A[i] \leftarrow s / (i + 1)$        $n$

**return**  $A$       1



# Arithmetic Progression

- ◆ The running time of *prefixAverages1* is  $O(1 + 2 + \dots + n)$
- ◆ The sum of the first  $n$  integers is  $n(n + 1) / 2$ 
  - There is a simple visual proof of this fact
- ◆ Thus, algorithm *prefixAverages1* runs in  $O(n^2)$  time



# Prefix Averages

- ◆ Asymptotic analysis tells us the complexity of the original algorithm.
- ◆ [TEAMS] Given such a tool, how can we make the algorithm more efficient?

# Prefix Averages (Linear)

- ◆ The following algorithm computes prefix averages in linear time by keeping a running sum

**Algorithm** *prefixAverages2*( $X, n$ )

**Input** array  $X$  of  $n$  integers

**Output** array  $A$  of prefix averages of  $X$

$A \leftarrow$  new array of  $n$  integers

$s \leftarrow 0$

**for**  $i \leftarrow 0$  **to**  $n - 1$  **do**

$s \leftarrow s + X[i]$

$A[i] \leftarrow s / (i + 1)$

**return**  $A$

#operations

$n$

1

$n$

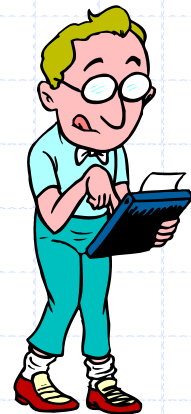
$n$

$n$

1

- ◆ Algorithm *prefixAverages2* runs in  $O(n)$  time

# Math you need to Review



- ◆ Summations
- ◆ Logarithms and Exponents

- ◆ **properties of logarithms:**

$$\log_b(xy) = \log_b x + \log_b y$$

$$\log_b (x/y) = \log_b x - \log_b y$$

$$\log_b x^a = a \log_b x$$

$$\log_b a = \log_x a / \log_x b$$

- ◆ **properties of exponentials:**

$$a^{(b+c)} = a^b a^c$$

$$a^{bc} = (a^b)^c$$

$$a^b / a^c = a^{(b-c)}$$

$$b = a^{\log_a b}$$

$$b^c = a^{c \cdot \log_a b}$$

- ◆ Proof techniques
- ◆ Basic probability

# Relatives of Big-Oh



## ◆ big-Omega

- $f(n)$  is  $\Omega(g(n))$  if there is a constant  $c > 0$  and an integer constant  $n_0 \geq 1$  such that  $f(n) \geq c \cdot g(n)$  for  $n \geq n_0$

## ◆ big-Theta

- $f(n)$  is  $\Theta(g(n))$  if there are constants  $c' > 0$  and  $c'' > 0$  and an integer constant  $n_0 \geq 1$  such that  $c' \cdot g(n) \leq f(n) \leq c'' \cdot g(n)$  for  $n \geq n_0$

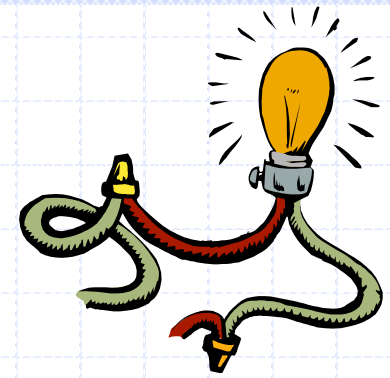
## ◆ little-oh

- $f(n)$  is  $o(g(n))$  if, for any constant  $c > 0$ , there is an integer constant  $n_0 \geq 0$  such that  $f(n) < c \cdot g(n)$  for  $n \geq n_0$

## ◆ little-omega

- $f(n)$  is  $\omega(g(n))$  if, for any constant  $c > 0$ , there is an integer constant  $n_0 \geq 0$  such that  $f(n) > c \cdot g(n)$  for  $n \geq n_0$

# Intuition for Asymptotic Notation



## Big-Oh

- $f(n)$  is  $O(g(n))$  if  $f(n)$  is asymptotically **less than or equal** to  $g(n)$

## big-Omega

- $f(n)$  is  $\Omega(g(n))$  if  $f(n)$  is asymptotically **greater than or equal** to  $g(n)$

## big-Theta

- $f(n)$  is  $\Theta(g(n))$  if  $f(n)$  is asymptotically **equal** to  $g(n)$

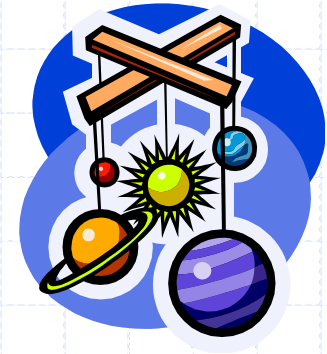
## little-oh

- $f(n)$  is  $o(g(n))$  if  $f(n)$  is asymptotically **strictly less** than  $g(n)$

## little-omega

- $f(n)$  is  $\omega(g(n))$  if is asymptotically **strictly greater** than  $g(n)$

# Example Uses of the Relatives of Big-Oh



## ■ $5n^2$ is $\Omega(n^2)$

$f(n)$  is  $\Omega(g(n))$  if there is a constant  $c > 0$  and an integer constant  $n_0 \geq 1$  such that  $f(n) \geq c \cdot g(n)$  for  $n \geq n_0$

[TEAMS] What are values for  $c$  and  $n_0$ ?

Let  $c = 5$  and  $n_0 = 1$

## ■ $5n^2$ is $\Omega(n)$

$f(n)$  is  $\Omega(g(n))$  if there is a constant  $c > 0$  and an integer constant  $n_0 \geq 1$  such that  $f(n) \geq c \cdot g(n)$  for  $n \geq n_0$

Let  $c = 1$  and  $n_0 = 1$

## ■ $5n^2$ is $\omega(n)$

$f(n)$  is  $\omega(g(n))$  if, for any constant  $c > 0$ , there is an integer constant  $n_0 \geq 0$  such that  $f(n) \geq c \cdot g(n)$  for  $n \geq n_0$

Need  $5n_0^2 > c \cdot n_0 \rightarrow$  given  $c$ , the  $n_0$  that satisfies this is  $n_0 > c/5 > 0$

# Euclid's Algorithm

- ◆ *An algorithm for computing the greatest common divisor (GCD) of two numbers  $M \geq N$ :*

**Algorithm GCD(M, N)**

**while** (N  $\neq$  0)

    rem  $\leftarrow$  M mod N

    M  $\leftarrow$  N

    N  $\leftarrow$  rem

**endwhile**

**return** M

- ◆ [TEAMS] What is the *Big-Oh*?



# Euclid's Algorithm

- ◆ *An algorithm for computing the greatest common divisor (GCD) of two numbers  $M \geq N$ :*

**Algorithm GCD(M, N)**

**while** (N  $\neq$  0)

    rem  $\leftarrow$  M mod N

    M  $\leftarrow$  N

    N  $\leftarrow$  rem

**endwhile**

**return** M

- ◆ The algorithm GCD runs is  $O(\log n)$

# Euclid's Algorithm

## ◆ Why?

- If  $M \geq N$ , then  $(M \bmod N) < M/2$
- Thus, each iteration at least halves the value of  $M$

# Exponentiation

◆ *A recursive algorithm to compute  $X$  to the power  $N$ :*

```
Algorithm pow(X, N)
  if (N == 0) return 1
  if (N == 1) return X
  if (N is even)
    return pow(X*X, N/2)
  else
    return pow(X*X, N/2) * X
```

1

◆ [TEAMS] What is the *Big-Oh*?

# Exponentiation

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- ◆ The algorithm *pow* is  $O(\log n)$