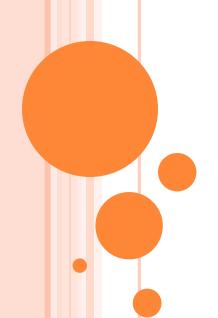




Jyh-Shing Roger Jang (張智星) CSIE Dept, National Taiwan University





Several Basic Functions

- Polynomial
 - Constant function 1.C
 - Linear function N: problem size
 - Quadratic function N²
 - Cubic function
- Logarithm function
- N-Log-N function NlogN
- Exponential function e^{^N}



Family of Polynomials

- Constant function
 - f(n)=1

n: problem size

- Linear function
 - f(n)=n
- Quadratic function
 - $f(n)=n^2$
- Cubic function
 - $f(n)=n^3$
- A general polynomials
 - $f(n)=a_0+a_1n+a_2n^2+a_3n^3+...+a_dn^d$



The Logarithm Function

 \circ f(n)=log₂(n)=log(n)

- The default base is 2.
- Definition of logarithm

$$x = \log_b n$$
 if and only if $b^x = n$.

Some identities

- $1. \log_b ac = \log_b a + \log_b c$
- $2. \log_b a/c = \log_b a \log_b c$
- 3. $\log_b a^c = c \log_b a$
- 4. $\log_b a = (\log_d a)/\log_d b$
- $5. b^{\log_d a} = a^{\log_d b}$
- More...

$$y = \ln x \Rightarrow y' = \frac{1}{x} \Rightarrow \int \frac{1}{x} dx = \ln x$$



The N-Log-N Function

o f(n)=n*log(n)



The Exponential Function

- \circ f(n)=aⁿ
- Some identities (for positive a, b, and c)

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

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

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

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

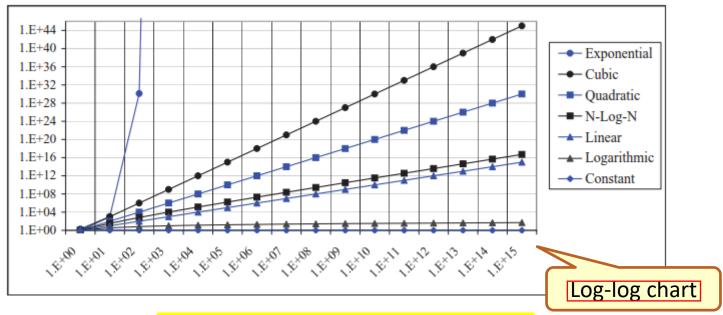
$$b^c = a^{c^* \log_a b}$$



Growth Rate Comparisons

conste	ant	logarithm	linear	n-log-n	quadratic	cubic	exponential
1		$\log n$	n	$n\log n$	n^2	n^3	a^n

Table 4.1: Classes of functions. Here we assume that a > 1 is a constant.

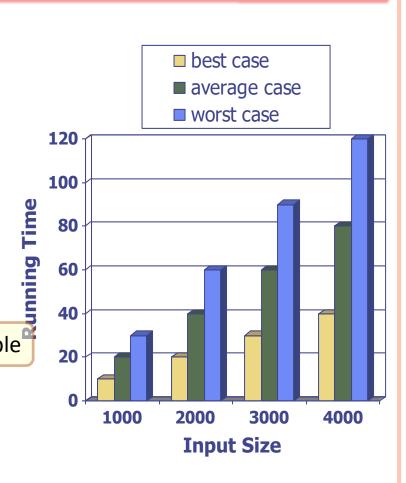


$$y = n^k \implies \log y = k \log n \implies Y = kX$$



Running Time

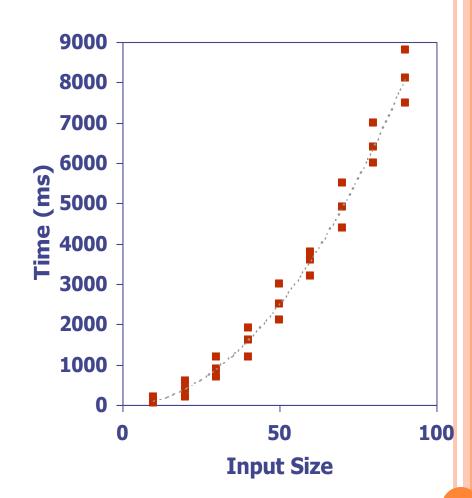
- Most algorithms transform input objects into output objects.
- The running time of an algorithm typically grows with the input size.
- Average case time is often difficult to determine.
- We focus on the worst case running time.
 - Easier to analyze
 - Crucial to applications such as games, finance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





Performance Measurement via Experiments

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





Limitations of Experimental Studies

- 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 Performance 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

ABOUT PRIMITIVE OPERATIONS

- 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

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



Counting Primitive Operations

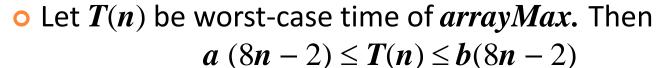
 By inspecting the pseudocode, we can determine the maximum number of primitive operations executed by an algorithm, as a function of the input size

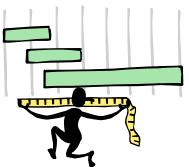
```
Algorithm arrayMax(A, n) # operations currentMax \leftarrow A[0] 2 A[0], assign 2n —路asign過去 if A[i] > currentMax then currentMax \leftarrow A[i] { increment counter i } 2(n-1) { return currentMax 1 Total 8n-2
```



Estimating Running Time

- Algorithm arrayMax executes 8n-2 primitive operations in the worst case. Define:
 - a = Time taken by the fastest primitive operation
 - b = Time taken by the slowest primitive operation





- \circ Hence, the running time T(n) is bounded by two linear functions
- Change the hardware environment only affects a and b.
- The linear growth rate of the running time T(n) is an intrinsic property of algorithm arrayMax



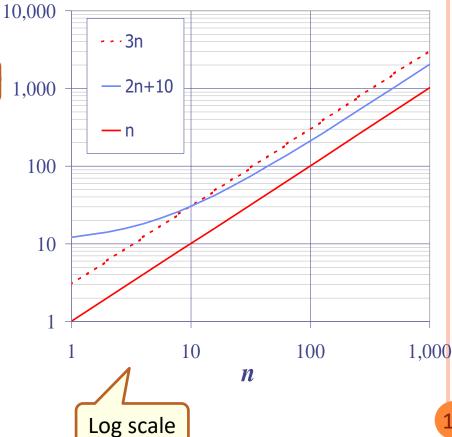
Big-Oh Notation

• 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

$$> f(n) \le cg(n)$$
 for $n \ge n_0$

- Example: 2n + 10 is O(n)
 - $2n + 10 \le cn$
 - $(c-2) n \ge 10$
 - $n \ge 10/(c-2)$
 - Pick c = 3 and $n_0 = 10$

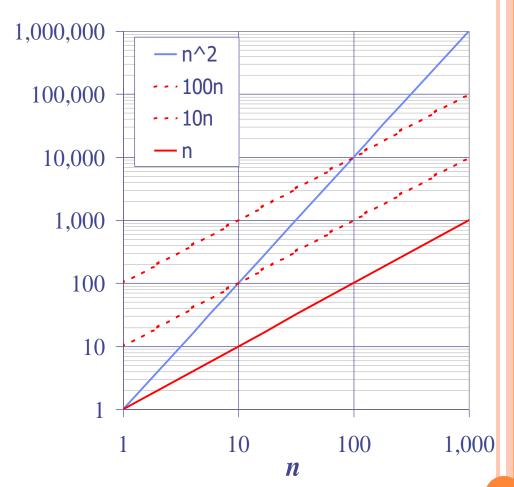
g(n): basic functions





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
 must be a constant





More Big-Oh Examples

- 7n-2 is O(n)
 - Need c > 0 and $n_0 \ge 1$ such that $7n-2 \le c \cdot n$ for $n \ge n_0$
 - This is true for c = 7 and $n_0 = 1$
- \circ 3n³ + 20n² + 5 is O(n³)
 - Need c > 0 and $n_0 \ge 1$ such that $3n^3 + 20n^2 + 5 \le c \cdot n^3$ for $n \ge n_0$ $3n^3 + 20n^3 + 5n^3 = 28n^3$
 - This is true for c = 28 and $n_0 = 1$
- 3 log n + 5 is O(log n)
 - Need c > 0 and $n_0 \ge 1$ such that 3 log n + 5 \le c•log n for $n \ge n_0$
 - This is true for c = 8 and $n_0 = 2$

Quiz!

 $3\log n + 5\log n = 8\log n$



Big-Oh Rules

- o If is f(n) 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

 That is when n is big!
- 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 8n
 2 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

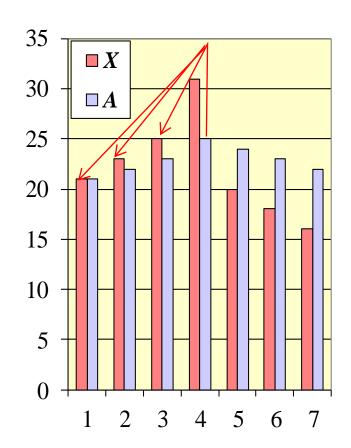


Computing Prefix Averages

- 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*:

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

 \circ 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 directly.

```
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
   for i \leftarrow 0 to n-1 do
        s \leftarrow X[0]
                                                1 + 2 + \ldots + (n - 1)
        for j \leftarrow 1 to i do
                                                1 + 2 + \ldots + (n-1)
                 s \leftarrow s + X[j]
        A[i] \leftarrow s / (i+1)
                                 n(n-1)/2
   return A
```



Prefix Averages (Linear)

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

Algorithm prefixAverages2(X, n)							
Input array <i>X</i> of <i>n</i> integers							
Output array A of prefix average	#operations						
$A \leftarrow$ new array of n integers	\boldsymbol{n}						
$s \leftarrow 0$	1						
for $i \leftarrow 0$ to $n-1$ do	\boldsymbol{n}						
$\rightarrow s \leftarrow s + X[i]$	\boldsymbol{n}						
$A[i] \leftarrow s / (i+1)$	n	\boldsymbol{n}					
return A	11	1					

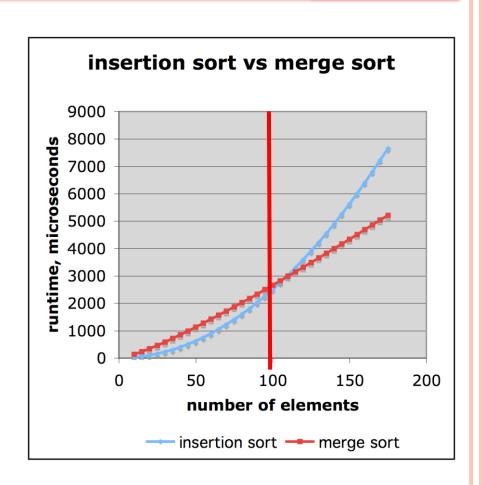


Comparison of Two Algorithms

- Two sorting algorithms
 - Merge sort is O(n log n)
 - Insertion sort is O(n²)
- To sort 1M items
 - Insertion sort 70 hours
 - Merge sort → 40 seconds
- For a faster machine

 - Merge sort → 0.5 seconds

Slide by Matt Stallmann





Relatives of Big-Oh

Big-Omega

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

Big-Theta

f(n) is Θ(g(n)) if there are constants c' > 0 and c'' > 0 and an integer constant n₀ ≥ 1 such that c'•g(n) ≤ f(n) ≤ c''•g(n) for n ≥ n₀



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)



Example Uses of the Relatives of Big-Oh

- \circ 5n² is $\Omega(n^2)$
 - f(n) is $\Omega(g(n))$ if there is a constant c > 0 and an integer constant $n_0 \ge 1$ such that $f(n) \ge c \cdot g(n)$ for $n \ge n_0 \longrightarrow \text{let } c = 5$ and $n_0 = 1$
- \circ 5n² is $O(n^2)$
 - f(n) is $\Omega(g(n))$ if there is a constant c > 0 and an integer constant $n_0 \ge 1$ such that $f(n) \le c \cdot g(n)$ for $n \ge n_0 \longrightarrow 1$ let c = 5 and $n_0 = 1$
- \circ 5 n^2 is $\Theta(n^2)$
 - f(n) is $\Theta(g(n))$ if it is $\Omega(n^2)$ and $O(n^2)$.



Computing Powers

- To compute the power function $p(x, n) = x^n$
 - Method 1
 - o n, n-1, n-2, ..., 2, 1 → O(n)

$$p(x,n) = \begin{cases} 1 & \text{if } n = 0 \\ x \cdot p(x,n-1) & \text{otherwise} \end{cases}$$

- Method 2
 - o n, n/2, n/4, ..., 2, 1 → O(log n)

$$p(x,n) = \begin{cases} 1 & \text{if } n = 0\\ x \cdot p(x,(n-1)/2)^2 & \text{if } n > 0 \text{ is odd}\\ p(x,n/2)^2 & \text{if } n > 0 \text{ is even} \end{cases}$$



Element Uniqueness Problem (1/2)

- To determine if the elements in a vector are all unique
 - O(2ⁿ) implementation by recursion

```
bool isUnique(const vector<int>& arr, int start, int end) {
   if (start >= end) return true;
   if (!isUnique(arr, start, end-1))
     return false;
   if (!isUnique(arr, start+1, end))
     return false;
   return (arr[start] != arr[end]);
}
```

O(n²) implementation by looping



Element Uniqueness Problem (2/2)

- To determine if the elements in a vector are all unique
 - O(n log n) implementation → Sort the vector first and check for neighboring duplicate elements

 A faster average-case running time can be achieved by using the hash table data structure (Section 9.2).



How to Prove Statements

By giving counter example

- Roger claims that every number of the form 2ⁱ-1 is a prime, where i is an integer greater than 1. Prove he is wrong.
- By contrapositive: Switching the hypothesis and conclusion of a conditional statement and negating both.
 - If p is true, then q is true ←→ If q is not true, then p is not true
 - If a*b is even, then a is even or b is even. ←→ If a is odd and b is odd, then a*b is odd.
 - Be aware of "DeMorgan's Law"

By math induction

Example: Prove that F(n)<2ⁿ, where F(n) is the Fibonacci function with F(n+2)=F(n+1)+F(n), and F(1)=1, F(2)=2.



Exercise on Big Oh

- Given functions f(n) and g(n), under what condition do we we say that f(n) is O(g(n))?
 - Note that g(n) is one of the basic functions, such as n³.
 - What is the physical meaning of the definition?
- Use the definition of big oh to explain why $3n^2+n\log(n)+2n+5\log(n)$ is $O(n^2)$.



Exercise on Proof by Induction

- Proof by induction
 - Prove that $F(n)<2^n$, where F(n) is the Fibonacci function satisfying F(n+2)=F(n+1)+F(n), with F(1)=1, F(2)=2.
- 3 steps in proof by induction
 - Base case
 - Inductive Hypothesis
 - Inductive Step