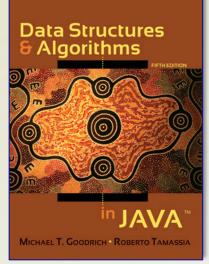
Data Structure & Algorithms in

JAVA

5th edition Michael T. Goodrich Roberto Tamassia



Chapter 4: Analysis Tools

CPSC 3200

Algorithm Analysis and Advanced Data Structure

Chapter Topics

- The Seven Functions.
- Analysis of Algorithms.
- Simple Justification Techniques.

How to analyze an algorithm

- To analyze an algorithm is to determine the amount of resources (such as time and storage) necessary to execute it.
- Most algorithms are designed to work with inputs of arbitrary length.
- Usually the efficiency or complexity of an algorithm is stated as a function relating the input length to the number of steps (time complexity) or storage locations.

Performance of a computer

- The performance of a computer is determined by:
- The hardware:
 - processor used (type and speed).
 - memory available (cache and RAM).
 - disk available.
- The programming language in which the algorithm is specified.
- The language compiler/interpreter used.
- The computer operating system software.

Performance of a Program

- The amount of computer memory and time needed to run a program.
 - Space complexity
 - Why?
 - Because We need to know the amount of memory to be allocated to the program.
 - Time complexity
 - Why?
 - Because We need upper limit on the amount of time needed by the program. (Real-Time systems)

Performance of a Program cont...

- Space Complexity
 - Instruction space (size of the compiled version)
 - Data space (constants, variables, arrays, etc.)
 - Environment stack space (context switching)
- Time Complexity
 - All the factors that space complexity depends on.
 - Compilation time
 - Execution time
 - Operation counts

What is an algorithm and why do we want to analyze one?

- An algorithm is "a step-by-step procedure for accomplishing some end." (solve a problem, complete a task, etc.)
- An algorithm can be given or expressed in many ways.
- For example, it can be written down in English (or French, or any other "natural" language).
- We seek algorithms which are *correct* and *efficient*.
- Correctness
 - For any algorithm, we must prove that it *always* returns the desired output for all legal instances of the problem.
- *Efficiency:* Minimum time and minimum resources.

But what can we analyze?

- determine the running time of a program as a function of its inputs.
- determine the total or maximum memory space needed for program data.
- determine the total size of the program code.
- determine whether the program correctly computes the desired result.
- determine the complexity of the program- e.g., how easy is it to read, understand, and modify.
- determine the robustness of the program- e.g., how well does it deal with unexpected or erroneous inputs?
- etc.

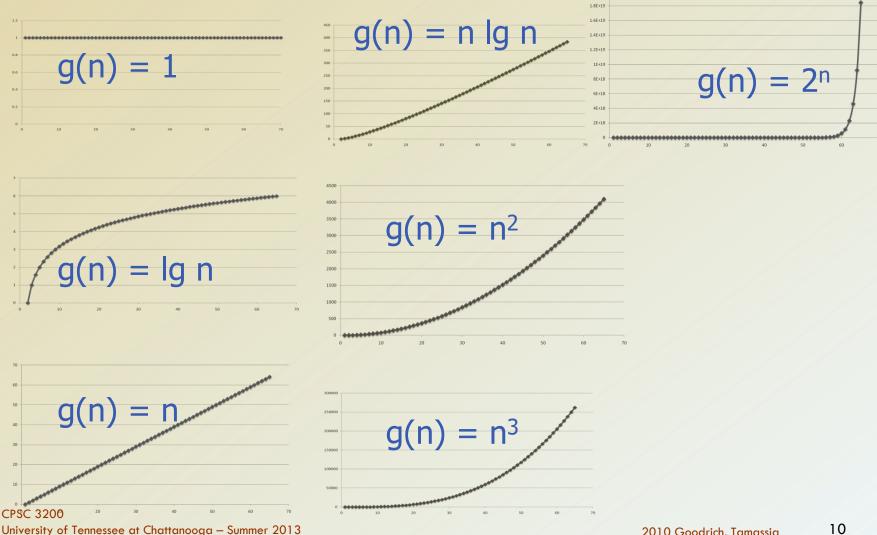
Seven Important Functions

- Seven functions that often appear in algorithm analysis:
 - Constant ≈ 1
 - Logarithmic $\approx \log n$
 - Linear $\approx n$
 - N-Log-N $\approx n \log n$
 - Quadratic $\approx n^2$
 - Cubic $\approx n^3$
 - Exponential $\approx 2^n$

Functions Graphed Using "Normal" Scale

Slide by Matt Stallmann included with permission.

2E+19



Proposition 4.1 (Logarithm Rules): Given real numbers a > 0, b > 1, c > 0 and d > 1, we have:

1.
$$\log_b ac = \log_b a + \log_b c$$

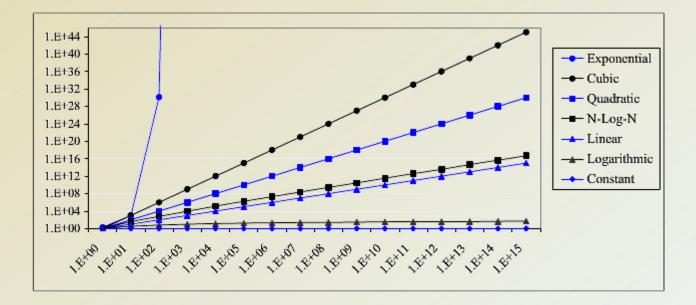
2. $\log_b a/c = \log_b a - \log_b c$
3. $\log_b a^c = c \log_b a$
4. $\log_b a = (\log_d a) / \log_d b$
5. $b^{\log_d a} = a^{\log_d b}$.

Example 4.2: We demonstrate below some interesting applications of the logarithm rules from Proposition 4.1 (using the usual convention that the base of a logarithm is 2 if it is omitted).

- $\log(2n) = \log 2 + \log n = 1 + \log n$, by rule 1
- $\log(n/2) = \log n \log 2 = \log n 1$, by rule 2
- $\log n^3 = 3\log n$, by rule 3
- $\log 2^n = n \log 2 = n \cdot 1 = n$, by rule 3
- $\log_4 n = (\log n) / \log 4 = (\log n) / 2$, by rule 4
- $2^{\log n} = n^{\log 2} = n^1 = n$, by rule 5.

Comparing Growth Rate

constant	logarithm	linear	n-log-n	quadratic	cubic	exponential
1	log n	n	n log n	n^2	n^3	a^n



Math you need to Review

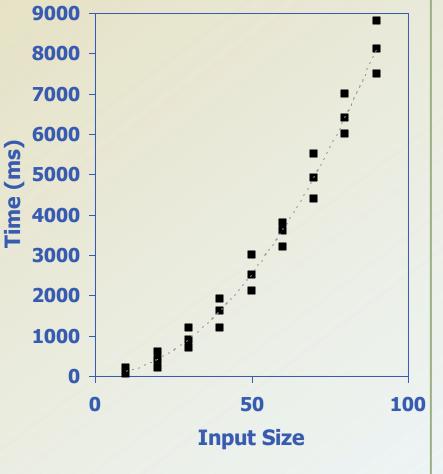
- Summations
- Logarithms and Exponents

- Proof techniques
- Basic probability

- properties of logarithms: log_b(xy) = log_bx + log_by log_b (x/y) = log_bx - log_by log_bxa = alog_bx log_ba = log_xa/log_xb
- properties of exponentials: $a^{(b+c)} = a^b a^c$ $a^{bc} = (a^b)^c$ $a^b / a^c = a^{(b-c)}$ $b = a^{\log_a b}$ $b^c = a^{c^* \log_a b}$

Experimental Studies

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



Limitations of Experiments

- 1. 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.
- **3.** 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 ← *A*[0] for *i* ← 1 to *n* − 1 do if *A*[*i*] > *currentMax* then *currentMax* ← *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 call var.method (arg [, arg...])
- Return value
 return expression
- Expressions
 - ← Assignment (like = in Java)
 - = Equality testing (like == in Java)
 - *n*² Superscripts and other mathematical formatting allowed

Primitive Operations

- Basic computations performed by an algorithm.
- Identifiable in pseudocode.
- Largely independent from the programming language.
- Exact definition not important.
- 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.

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.

4000

3000

best case

120

100

80

60

40

20

1000

2000

Input Size

Sunning Time

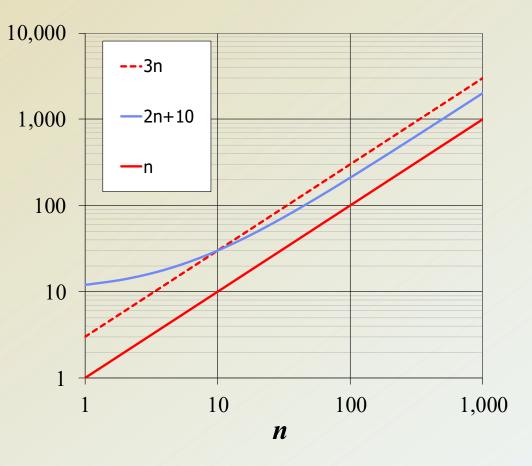
average case
 worst case

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 n₀ such that

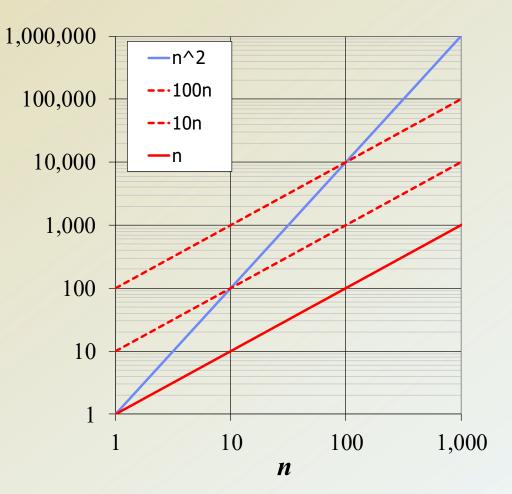
 $f(n) \leq cg(n)$ for $n \geq n_0$

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



Big-Oh Example

- Example: the function
 n² is not O(n)
 - $n^2 \leq cn$
 - *n* ≤ *c*
 - The above inequality cannot be satisfied since *c* must be a constant.



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

$\begin{array}{l} \textbf{Algorithm} arrayMax(A, n) \\ currentMax \leftarrow A[0] \end{array}$	# o	perations 2
for <i>i</i> ← 1 to <i>n</i> − 1 do		2 n
if A[i] > currentMax then		2(n – 1)
$currentMax \leftarrow A[i]$		2(n − 1)
{ increment counter <i>i</i> }		2 (<i>n</i> − 1)
return <i>currentMax</i>		1
	Total	8 n – 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

- Let T(n) be worst-case time of *arrayMax*. Then $a(8n-2) \le T(n) \le b(8n-2)$
- Hence, the running time *T*(*n*) is bounded by two linear functions.

Big-Oh Rules

If *f*(*n*) a polynomial of degree *d*, then *f*(*n*) is
 O(*n^d*), i.e.,

Drop lower-order terms.
 Drop constant factors.

- Use the smallest possible class of functions
 - Say "2*n* is *O*(*n*)" instead of "2*n* is *O*(*n*²)"
- Use the simplest expression of the class
 - Say "3n + 5 is O(n)" instead of "3n + 5 is O(3n)"

More Big-Oh Examples

- 7n-2
 - 7n-2 is O(n)
 - **need c > 0 and n_0 \ge 1 such that 7n-2 \le c \bullet n for n \ge n_0**
 - this is true for c = 7 and $n_0 = 1$
- $3n^3 + 20n^2 + 5$
 - $3n^3 + 20n^2 + 5$ is $O(n^3)$
 - need c > 0 and $n_0 \ge 1$ such that $3n^3 + 20n^2 + 5 \le c \bullet n^3$ for $n \ge n_0$ this is true for c = 4 and $n_0 = 21$

3 log n + 5

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 $n_0 = 2$

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 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.

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 $O(g(n))$	<i>g</i> (<i>n</i>) is <i>O</i> (<i>f</i> (<i>n</i>))
g(n) grows more	Yes	No
f(n) grows more	No	Yes
Same growth	Yes	Yes

Asymptotic Analysis

n	log n	п	n log n	n^2	n ³	2^n
8	3	8	24	64	512	256
16	4	16	64	256	4,096	65,536
32	5	32	160	1,024	32,768	4,294,967,296
64	6	64	384	4,096	262,144	1.84×10^{19}
128	7	128	896	16,384	2,097,152	3.40×10^{38}
256	8	256	2,048	65,536	16,777,216	1.15×10^{77}
512	9	512	4,608	262,144	134,217,728	1.34×10^{154}

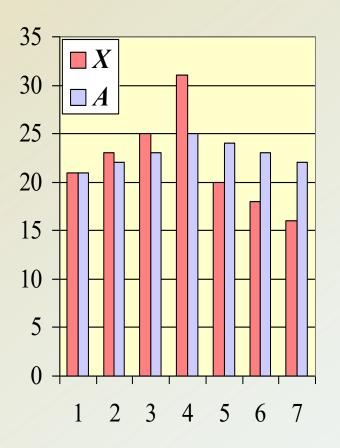
Running	Maximum Problem Size (n)				
Time (µs)	1 second	1 minute	1 hour		
400 <i>n</i>	2,500	150,000	9,000,000		
$2n^2$	707	5,477	42,426		
2^n	19	25	31		

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)

• 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
   A \leftarrow new array of n integers
   for i \leftarrow 0 to n - 1 do
         s \leftarrow X[0]
         for j \leftarrow 1 to i do
                  s \leftarrow s + X[j]
        A[i] \leftarrow s/(i+1)
   return A
```

Arithmetic Progression

- The running time of *prefixAverages1* is *O*(1 + 2 + ...+ *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 (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
```

Computing Power - Recursive

Algorithm Power(x,n): **Input:** A number x and integer $n \ge 0$ $O(\log n)$ **Output:** The value xn **if** n = 0 **then** return 1 if n is odd then $y \leftarrow Power(x,(n-1)/2)$ $p(x,n) = \begin{cases} 1 & \text{if } n = 0\\ x \cdot p(x,n-1) & \text{otherwise.} \end{cases}$ return x·y·y else $p(x,n) = \begin{cases} 1 & \text{if } n = 0 \\ x \cdot p(x,(n-1)/2)^2 & \text{if } n > 0 \text{ is odd} \\ p(x,n/2)^2 & \text{if } n > 0 \text{ is even.} \end{cases}$ $y \leftarrow Power(x,n/2)$ return y·y

Constant Time Method

public static int capacity(int[] arr)

O(1)

{

}

Finding the Maximum in an Array

```
public static int findMax(int[] arr)
{
    int max = arr[0]; // start with the first integer in arr
    for (int i=1; i < arr.length; i++)
        if (max < arr[i])
            max = arr[i]; // update the current maximum
        return max; // the current maximum is now the
            global maximum</pre>
```

O(n)

Simple Justification Techiniques

1. By Example.

- Counter Example.
- 2ⁱ 1 is prime !!!
- 2. The "Contra" Attack.
 - Contrapositive.
 - If *ab* is even, then *a* is even, or *b* is even.
 - Contradiction.
 - If *ab* is odd, then *a* is odd, and *b* is odd.
- **3. Induction and Loop Invariants.**

End of Chapter 4