#### Introduction to Data Structures ICS 240

Jessica Maistrovich

Metropolitan State University

# Complexity Analysis

## Introduction to Runtime Analysis

An algorithm is a step-by-step procedure for solving a problem in a finite amount



- Goal: Given two algorithms, which one is better?
- Criteria?

Faster?

- Smaller? (less memory)
- Easier to implement? Easier to maintain?
- Worst case?
- Average case?
- The study of algorithm efficiency is called complexity analysis
- In ICS 240, we will focus primarily on which algorithm is faster
- Runtime analysis of an algorithm is a method that is used to estimate the running time of an algorithm

### How Long Will My Algorithm Take to Solve the Problem: Approach I

- There are different approaches to measure how long an algorithm takes
- Implement the algorithm, execute it, and use a stop watch to measure
- Issues with this method:
- Time consuming: You need to implement the algorithm first, wasting time if you discover the algorithm is not efficient
- There are external factors that affect time taken by the algorithm (e.g., hardware, compiler, libraries)
- the algorithm may take different time if run on a different computer
- What about input data sets that were not tested?
- The algorithm may take different time if you change the input data or size of data

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### How Long Will My Algorithm Take to Solve the Problem (continued): Approach 2

- Count the operations the algorithm performs
- Count the number of operations that are performed for a given input size (e.g., number of items stored in an array)
- uses a high-level description of the algorithm instead of an implementation in a programming
- Characterize running time as a function of the input size (commonly represented as variable N
- Characterize how the number of operations changes as N changes
- This method of evaluation is independent of the actual input or implementation environment

#### Goal

Characterize how algorithm performance changes as the input size (N) changes

#### Two algorithms

```
currentMax = arr[i];
Find the maximum element in a bag of integers
                               static int findMax(int[] arr, int N) {
                                                                   int currentMax = arr[0];
for (int i= 0; i < N; i++)
   if (currentMax < arr[i]</pre>
                                                                                                                                                                                                         return currentMax;
```

```
Counting operations:
```

Line 1: method signature: no time

• Lines 2 and 3: 1 operation each(assignment) for a total of 2 operations

Line 3: loop iterates N times - so we will multiply N by the count of the loop body

**Lines 4 and 5:** 4 operations (<, =, <, ++)

Line 6: 1 operation (return)

Total:  $2 + (N)^4 + 1 = 4N + 3$ 

## Two algorithms (continued)

```
Find the maximum element in an <u>ordered list of</u>
integers
                                                         static int findMax(int[] arr, int N) {
                                                                                      return arr[N-1];
```

- Counting operations:
- Line 1: method signature: no time
- Line 2: 1 operation (return)
- Total: always 1 (independent of number of elements in the list)

### Which of the two algorithms leads to a better approach to finding max?

### Big-O Notation

#### $\leftarrow$

## Introducing Big-O Notation

- Big-O notation is used in Computer Science to describe the performance or complexity of an algorithm
- Big-O classes of algorithms:
- O(1) constant time algorithm
- The performance of the algorithm does not depend on input size
- O(N) -- linear time algorithm
- The performance of the algorithm changes linearly (in direct proportion) as the input size grows
- O(N²) quadratic time algorithm
- The performance of the algorithm changes as the square of the input size
- If two algorithms perform the same task with different big-O times, then with sufficiently large input, the algorithm with the better big-O analysis will perform faster
- Big-O notation approximates performance

## Common Big-O Functions

#### grows more slowly



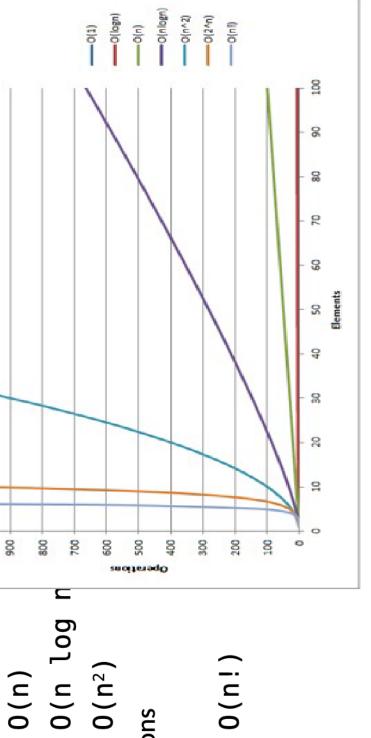
Big-O Complexity

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O(log n)

0(1)





grows faster

# Asymptotic Growth Rates by Numbers

ပ	log n	u	n log n	n <sup>2</sup>	n <sub>3</sub>	2 <sup>n</sup>	n!
1000	0	1	0	7	1	2	_
1000	_	2	2	4	8	4	2
1000	2	4	8	16	64	16	24
1000	3	80	24	64	512	256	40320
1000	4	16	64	256	4096	65536	2.092E+13
1000	5	32	160	1024	32768	4294967296	2.631E+35
1000	9	64	384	4096	262144	1.84467E+19	1.269E+89
1000	7	128	968	16384	2097152	3.40282E+38	3.86E+215
1000	8	256	2048	65536	16777216	1.15792E+77	#NOM!

## **Big-O Notation Simplification**

Drop constants:

• 1,000,000 = 1 \* 1,000,000 = 0(1)

A million is big-O of 1

We do not worry about constants because they do not change as the input size change

Keep only the dominant term (fastest growing term)

3n + 5 is O(n)

3n + 5 = O(3n) - ignore 5 because 3n is the dominant term

O(3n) = O(n) - drop constants

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#### **Examples**

```
• f(n) = 4n^2
```

• 
$$f(n) = 50n^3 + 20n + 4$$

• We say that 
$$f(n)$$
 is  $O(n^3)$ 

• However, this is not useful, as 
$$n^3$$
 exceeds by far n, for large values

- It is also true to say f(n) is 0(n<sup>5</sup>)
- However, we should be as close as possible to f(n)

### Consider the function $g(n) = 100 + n^2 + 2^n$ . Which of the following is true:

• 
$$g(n) = O(1)$$

• 
$$g(n) = O(n^2)$$

• 
$$g(n) = O(2^n)$$

 $2*N^3 + 200*N + 52$ 

#### Try it!

spent by an algorithm for solving a problem of size n. Select the dominant term(s) having the steepest increase in n and specify the lowest Big-Oh Assume that each of the expressions below gives the processing time T(n)complexity of each algorithm.

Dominant term(s) O()
Dominant term(s)
Comman
-
Expression $5 + 0.001n^3 + 0.025n$ $500n + 100n^{1.5} + 50n \log_{10} n$ $0.3n + 5n^{1.5} + 2.5 \cdot n^{1.75}$ $n^2 \log_2 n + n(\log_2 n)^2$
Expression $5 + 0.001n^3 + 0.025n$ $500n + 100n^{1.5} + 50n \log$ $0.3n + 5n^{1.5} + 2.5 \cdot n^{1.75}$ $n^2 \log_2 n + n(\log_2 n)^2$
Expression $5 + 0.001n^3$ 500n + 100 $0.3n + 5n^1$ $n^2 \log_2 n +$

### Answers to Try it:

$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Expression	Dominant term(s)	(···)
$\begin{array}{lll} 5 + 50 n \log_{10} n & 100 n^{1.5} \\ -2.5 \cdot n^{1.75} & 2.5 n^{1.75} \\ \log_2 n)^2 & n^2 \log_2 n \\ \log_2 \log_2 n & n \log_3 n, n \log_2 n \\ \log_2 \log_2 n & 3 \log_8 n \\ \log_2 \log_2 n & 0.01 n^2 \\ & & & & & & & \\ 5n^{1.25} & & & & & & \\ n(\log_2 n)^2 & & & & & \\ n^3 + 100 n & & & & & \\ \log_2 \log_2 n & & & & & \\ n^3 + 100 n & & & & & \\ \end{array}$	$5 + 0.001n^3 + 0.025n$	$0.001n^{3}$	$O(n^3)$
	$500n + 100n^{1.5} + 50n \log_{10} n$	$100n^{1.5}$	$O(n^{1.5})$
	$0.3n + 5n^{1.5} + 2.5 \cdot n^{1.75}$	$2.5n^{1.75}$	$O(n^{1.75})$
$g_2 n$ $n \log_3 n, n \log_2 n$ $\log_2 \log_2 n$ $3 \log_8 n$ $5n^{1.25}$ $0.01n^2$ $n(\log_2 n)^2$ $n(\log_2 n)^2$ $n^3 + 100n$ $n^3$ $\log_2 \log_2 n$ $n^3$ $\log_2 \log_2 n$ $n^3$ $\log_2 \log_2 n$ $n^3$	$n^2 \log_2 n + n(\log_2 n)^2$	$n^2 \log_2 n$	$O(n^2 \log n)$
$\log_2 \log_2 n$ $3 \log_8 n$ $0.01n^2$ $5n^{1.25}$ $100n^2$ $n(\log_2 n)^2$ $n(\log_2 n)^2$ $n^3 + 100n$ $n^3$ $\log_2 \log_2 n$ $0.003 \log_4 n$	$n \log_3 n + n \log_2 n$	$n \log_3 n,  n \log_2 n$	$O(n \log n)$
$\begin{array}{ccc} 0.01n^2 \\ 5n^{1.25} \\ n(\log_2 n)^2 \\ n^3 + 100n \\ \log_2 \log_2 n \\ \log_2 \log_2 n \\ \end{array}$	$3\log_8 n + \log_2 \log_2 \log_2 n$	$3\log_8 n$	$O(\log n)$
$   \begin{array}{ccc}     100n^2 \\     5n^{1.25} & 0.5n^{1.25} \\     n(\log_2 n)^2 & n(\log_2 n)^2 \\     n^3 + 100n & n^3 \\     \log_2 \log_2 n & 0.003 \log_4 n   \end{array} $	$100n + 0.01n^2$	$0.01n^{2}$	$O(n^2)$
$0.5n^{1.25}$ $n(\log_2 n)^2$ $n^3$ $0.003 \log_4 n$	$0.01n + 100n^2$	$100n^{2}$	$O(n^2)$
$\frac{n(\log_2 n)^2}{n^3}$ $0.003 \log_4 n$	$2n + n^{0.5} + 0.5n^{1.25}$	$0.5n^{1.25}$	$O(n^{1.25})$
$n^3$ $0.003\log_4 n$		$n(\log_2 n)^2$	$O(n(\log n)^2)$
$0.003\log_4 n$		$n^3$	$O(n^3)$
	$0.003\log_4 n + \log_2\log_2 n$	$0.003\log_4 n$	$O(\log n)$

```
for (int i=0; i < N-3; i++) {
System.out.println (N);
```

```
System.out.println(2);
                       } else
```

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#### Example 1

- Assume you are given an array, OriginalArr
- Compute another array, averageArr, such that, for each value of i, averageArr[i] is the average of all elements in positions 0 to i inoriginalArr

	(10+20)/2	(10+20+30)/3	(10+20+30+40)/4	(10+20+30+40+50)/5	(10+20+30+40+50+60
10	15	20	25	30	35
10	20	30	40	50	60
	-	•	•		

originalArr

### Example 1 Algorithms

Usually, there is more than one way to solve a given problem

#### Solution 1

#### **Solution 2**

```
int sum;
for (int i=0; i < numItems; i++) {
    sum = 0;
    for (int j = 0; j <=i; j++) {
        sum = sum + originalArr[j];
        averageArr[i] = sum / (i+1);
    }
}</pre>
```

```
int sum = 0;
for (int i=0 ; i < numItems; i++) {
    sum = sum + originalArr[i];
    averageArr[i] = sum;
}
for (int i=0 ; i < numItems; i++)
    averageArr[i] = averageArr[i] / (i+1);</pre>
```

### Which solution is faster? Why?

#### Example 1

Usually, there is more than one way to solve a given problem.

#### Solution 1

#### **Solution 2**

```
averageArr[i] = sum / (i+1);
                                                                                                                   sum = sum + originalArr[j];
                         for (int i=0 ; i < numItems; i++){
                                                                                   for (int j = 0; j <=i; j++){
                                                          snm = 0;
int sum;
```

```
int sum = 0;
int[] averageArr = new
int[originalArr.length];
for (int i=0 ; i < numItems; i++){
   sum = sum + originalArr[i];
   averageArr[i] = sum;
}
for (int i=0 ; i < numItems; i++)
   averageArr[i] = averageArr[i] / (i+1);
```





```
for (int j = N; j > 0; j = j/10) {
```

```
System.out.println (j);
```

```
for (int k=1; k < N+3; k++) {
```

```
for (int m = N; m > 0; m--) {
```

```
System.out.println(m*k);
```

```
~~
```

```
for (int i = 1; i < 14; i++) {

for (int j=N; j > 1; j--) {

if (i%2 == 0) {

    System.out.println(i*j);

    }

}
```

#### Try it:

Work out the computational complexity of the following piece of code:

```
for( int i = n; i > 0; i /= 2 ) {
    for( int j = 1; j < n; j *= 2 ) {
        for( int k = 0; k < n; k += 2 ) {
            ... // constant number of operations
    }
}</pre>
```

Work out the computational complexity of the following piece of code.

```
for ( i=1; i < n; i *= 2 ) {
   for ( j = n; j > 0; j /= 2 ) {
    for ( k = j; k < n; k += 2 ) {
       sum += (i + j * k );
   }
}</pre>
```

 Work out the computational complexity of the following piece of code assuming that n = 2<sup>m</sup>:

```
for( int i = n; i > 0; i-- ) {
   for( int j = 1; j < n; j *= 2 ) {
     for( int k = 0; k < j; k++ ) {
        ... // constant number C of operations
   }
}</pre>
```

#### Try it!

4. Work out the computational complexity (in the "Big-Oh" sense) of the following piece of code and explain how you derived it using the basic features of the "Big-Oh" notation:

```
for( int bound = 1; bound <= n; bound *= 2 ) {
    for( int i = 0; i < bound; i++ ) {
        for( int j = 0; j < n; j += 2 ) {
            ... // constant number of operations
    }
    for( int j = 1; j < n; j *= 2 ) {
            ... // constant number of operations
    }
}
</pre>
```

### Answers to Try it:

- 1. In the outer for-loop, the variable i keeps halving so it goes round  $\log_2 n$  times. For each i, next loop goes round also  $\log_2 n$  times, because of doubling the variable j. The innermost loop by k goes round  $\frac{n}{2}$  times. Loops are nested, so the bounds may be multiplied to give that the algorithm is  $O\left(n(\log n)^2\right)$ .
- Running time of the inner, middle, and outer loop is proportional to n, log n, and log n, respectively. Thus the overall Big-Oh complexity is O(n(log n)<sup>2</sup>).

More detailed optional analysis gives the same value. Let  $n = 2^k$ . Then the outer loop is executed k times, the middle loop is executed k + 1 times, and for each value  $j = 2^k, 2^{k-1}, \ldots, 2, 1$ , the inner loop has different

$$\begin{array}{cccc} j & \text{Inner iterations} \\ 2^k & 1 \\ 2^{k-1} & (2^k - 2^{k-1}) \frac{1}{2} \\ 2^{k-2} & (2^k - 2^{k-2}) \frac{1}{2} \\ & \cdots & \cdots \\ 2^1 & (2^k - 2^1) \frac{1}{2} \\ 2^0 & (2^k - 2^0) \frac{1}{2} \\ \end{array}$$

In total, the number of inner/middle steps is

$$1 + k \cdot 2^{k-1} - (1+2+\ldots+2^{k-1})\frac{1}{2} = 1 + k \cdot 2^{k-1} - (2^k - 1)\frac{1}{2}$$
$$= 1.5 + (k-1) \cdot 2^{k-1} \equiv (\log_2 n - 1)\frac{n}{2}$$
$$= O(n\log n)$$

Thus, the total complexity is  $O(n(\log n)^2)$ .

### Answers to Try it:

- the innermost loop by k goes round j times, so that the two inner loops are nested, so the bounds may be multiplied to give that the algorithm is The outer for-loop goes round n times. For each i, the next loop goes together go round  $1 + 2 + 4 + ... + 2^{m-1} = 2^m - 1 \approx n$  times. Loops round  $m = \log_2 n$  times, because of doubling the variable j. For each j,
- and O(n), so a straightforward (and valid) solution is that the overall complexity, respectively. Thus, the overall complexity of the innermost part is O(n). The outermost and middle loops have complexity  $O(\log n)$  The first and second successive innermost loops have O(n) and O(log n) complexity is  $O(n^2 \log n)$ .