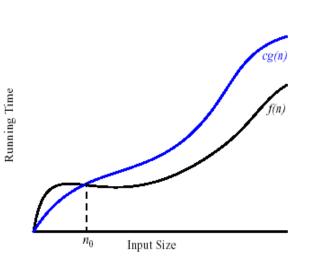
Q1-3



## CSSE 230 Day 2

#### Growable Arrays Continued Big-Oh and its cousins

#### Submit Growable Array exercise Answer Q1-3 from today's in-class quiz.

### Agenda and goals

- Finish course intro
- Growable Array recap
- Big-Oh and cousins
- After today, you'll be able to
  - Use the term *amortized* appropriately in analysis
  - explain the meaning of big-Oh, big-Omega ( $\Omega$ ), and big-Theta ( $\theta$ )
  - apply the definition of big-Oh to prove runtimes of functions

#### Announcements and FAQ

- Job opportunity!
  - Workstudy student to straighten up F217 and F225 labs each morning for ~1 hour/day. Let me or Darryl Mouck know if interested
- ▶ The game of Go: AI beating Lee Sodol, 2–0
  - Compare with checkers, chess.
  - <u>https://deepmind.com/alpha-go.html</u>
- Remind all do piazza post (3-4 students/section left)
- Late days?
- Test policy: Individual competence requirement

You must demonstrate programming competence on exams to succeed

- > See syllabus for exam weighting and caveats.
- Think of every program you write as a practice test
  - Especially HW4 and test 2a

#### Warm Up and Stretching thoughts

- Short but intense! ~45 lines of code total in our solutions to all but Adder
- Be sure to read the description of how it will be graded. Note how style will be graded.
- Demo: Running the JUnit tests for test, file, package, and project

Demo: Run the Adder program

#### Homework 1 help

Examples. How many times does sum++ run?

```
for (i = 4; i < n; i++)
sum++;
```

```
for (i = 1; i <= n; i *= 2)
sum++;
```

## Questions?

- About Homework 1?
  - Aim to complete tonight, since it is due after next class
  - It is substantial
- About the Syllabus?

#### Growable Arrays Exercise Daring to double

#### **Growable Arrays Table**

Ν	E <sub>N</sub>	Answers for problem 2
4	0	0
5	0	0
6	5	5
7	5	5 + 6 = 11
10	5	5 + 6 + 7 + 8 + 9 = 35
11	5 + 10 = 15	5 + 6 + 7 + 8 + 9 + 10 = 45
20	15	sum(i, i=519) = 180 using Maple
21	5 + 10 + 20 = 35	sum(i, i=520) = 200
40	35	sum(i, i=539) = 770
41	5 + 10 + 20 + 40 = 75	sum(i, i=540) = 810

## **Doubling the Size**

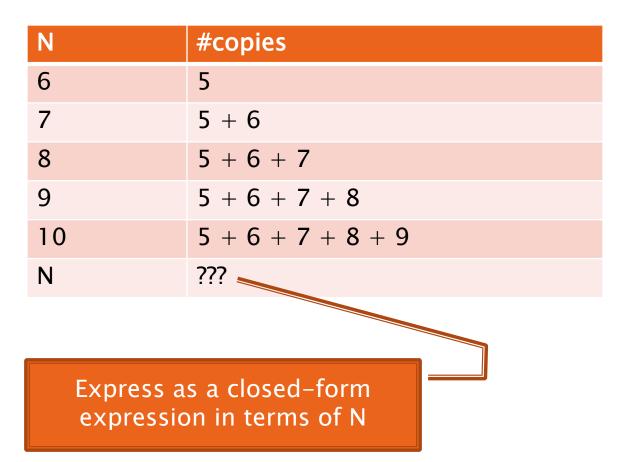
- Doubling each time:
  - Assume that  $N = 5 (2^k) + 1$ .
- Total # of array elements copied:

k	Ν	#copies
0	6	5
1	11	5 + 10 = 15
2	21	5 + 10 + 20 = 35
3	41	5 + 10 + 20 + 40 = 75
4	81	5 + 10 + 20 + 40 + 80 = 155
k	$= 5 (2^k) + 1$	$5(1 + 2 + 4 + 8 + + 2^k)$

Express as a closed-form expression in terms of K, then express in terms of N

#### Adding One Each Time

Total # of array elements copied:



#### Conclusions

- What's the average overhead cost of adding an additional string...
  - in the doubling case?
  - in the add-one case?

This is called the <mark>amortized</mark> cost

So which should we use?

## More math review

#### Review these as needed

- Logarithms and Exponents
  - properties of logarithms:

$$log_{b}(xy) = log_{b}x + log_{b}y$$
$$log_{b}(x/y) = log_{b}x - log_{b}y$$
$$log_{b}x^{\alpha} = \alpha log_{b}x$$
$$log_{b}x = \frac{log_{a}x}{log_{a}b}$$

- properties of exponentials:

$$a^{(b+c)} = a^{b}a^{c}$$
$$a^{bc} = (a^{b})^{c}$$
$$a^{b}/a^{c} = a^{(b-c)}$$
$$b = a^{\log_{a}b}$$
$$b^{c} = a^{c*\log_{a}b}$$

Practice with exponentials and logs (Do these with a friend after class, not to turn in)

Simplify: Note that  $\log n$  (without a specified) base means  $\log_2 n$ . Also,  $\log n$  is an abbreviation for  $\log(n)$ .

- **1.** log (2 n log n)
- 2.  $\log(n/2)$
- **3.** log (sqrt (n))
- 4. log (log (sqrt(n)))

Where do logs come from in algorithm analysis?

#### Solutions No peeking!

**Simplify:** Note that  $\log n$  (without a specified) base means  $\log_2 n$ . Also, log n is an abbreviation for  $\log(n)$ .

- 1.  $1 + \log n + \log \log n$
- 2. log n 1
- 3.  $\frac{1}{2} \log n$
- 4.  $-1 + \log \log n$

5. 
$$(\log n) / 2$$

6. 
$$n^2$$

7. 
$$n+1=2^{3k}$$
  
log(n+1)=3k

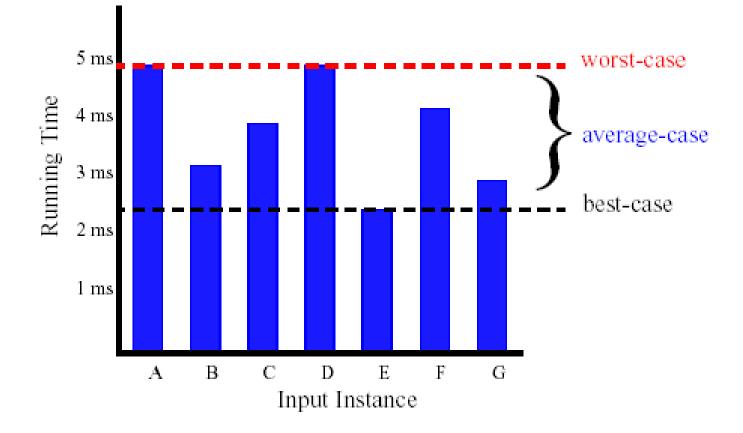
$$k = \log(n+1)/3$$

A: Any time we cut things in half at each step (like binary search or mergesort)

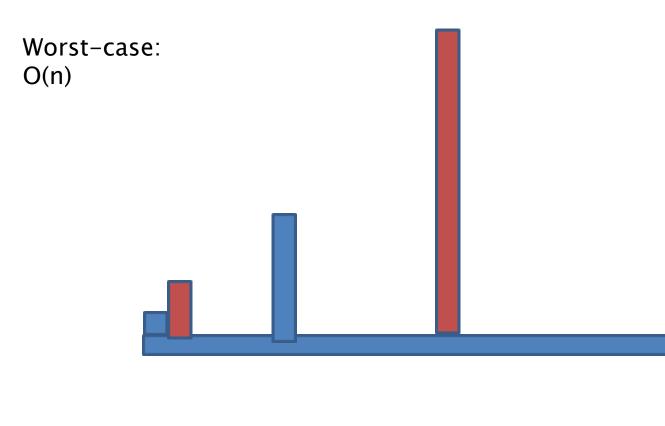
#### **Running Times**

- Algorithms may have different *time* complexity on different data sets
- What do we mean by "Worst Case"?
- What do we mean by "Average Case"?
- What are some application domains where knowing the Worst Case time complexity would be important?
- http://cacm.acm.org/magazines/2013/2/160173-the-tailat-scale/fulltext

#### Average Case and Worst Case



# Worst-case vs amortized cost for adding an element to an array using the doubling scheme





## Asymptotics: The "Big" Three

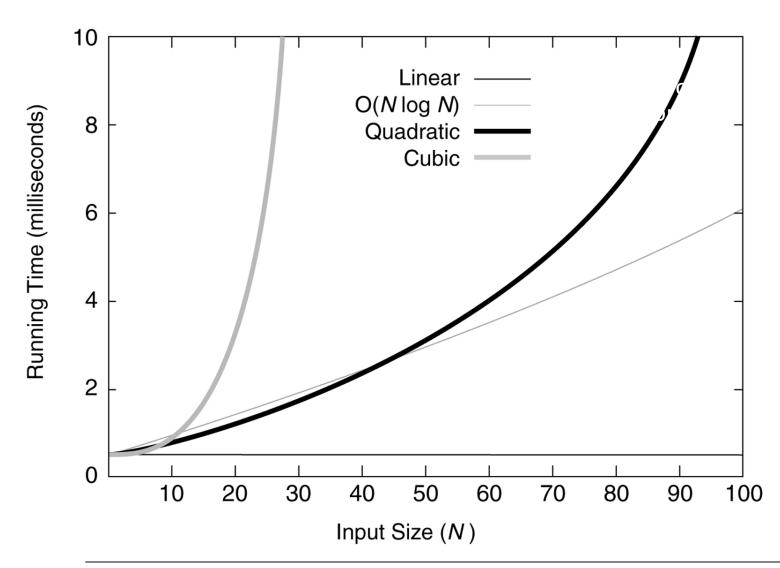
Big-Oh Big-Omega Big-Theta

#### Asymptotic Analysis

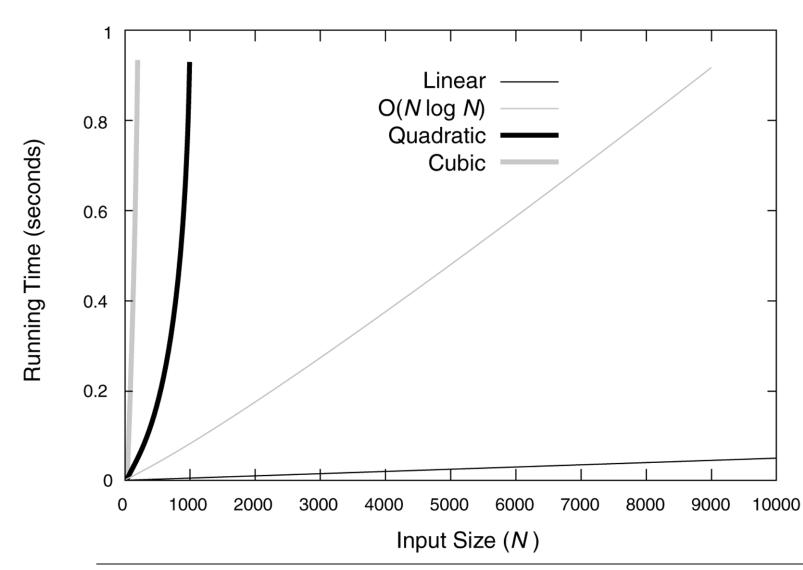
• We only care what happens when N gets large

Is the function linear? quadratic? exponential?

#### Figure 5.1 Running times for small inputs



#### **Figure 5.2** Running times for moderate inputs



#### **Figure 5.3** Functions in order of increasing growth rate

		The answer to most big-
Function	Name	Oh questions is one of
с	Constant	these functions
$\log N$	Logarithmic	
$\log^2 N$	Log-squared	
Ν	Linear	
$N \log N$	N log N	a.k.a "log linear"
N <sup>2</sup>	Quadratic	
N <sup>3</sup>	Cubic	
$2^N$	Exponential	

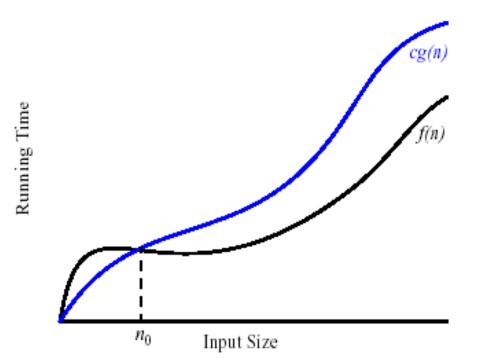
#### Simple Rule for Big-Oh

Drop lower order terms and constant factors

- ▶ 7n 3 is O(n)
- $\mathbf{N} = \mathbf{N}^2 + \mathbf{n} + \mathbf{n}$

## **Definition of Big-Oh**

- Given functions f(n) and g(n), we say that f(n) is O(g(n)) if and only if  $f(n) \le c g(n)$  for all  $n \ge n_0$ .
- Two constants: c > 0 is a real number and  $n_0 \ge 0$  is an integer.
- f(n) and g(n) are functions over non-negative integers.



#### To prove Big Oh, find 2 constants

- A function f(n) is (in) O(g(n)) if there exist two positive constants c and n<sub>0</sub> such that for all n≥ n<sub>0</sub>, f(n) ≤ c g(n)
- So all we must do to prove that f(n) is O(g(n)) is produce two such constants.
- f(n) = 4n + 15, g(n) = ???.

• 
$$f(n) = n + sin(n), g(n) = ???$$

Assume that all functions have non-negative values, and that we only care about  $n \ge 0$ . For any function g(n), O(g(n)) is a set of functions.

# Big-Oh, Big-Omega and Big-Theta O() $\Omega()$ $\theta()$

- ▶ f(n) is O(g(n)) if f(n)  $\leq$  cg(n) for all n  $\geq$  n<sub>0</sub>  $\circ$  So big-Oh (O) gives an upper bound
- f(n) is  $\Omega(g(n))$  if  $f(n) \ge cg(n)$  for all  $n \ge n_0$ • So big-omega ( $\Omega$ ) gives a lower bound
- f(n) is θ(g(n)) if it is both O(g(n) and Ω(g(n))
   Or equivalently:
- f(n) is  $\theta(g(n))$  if  $c_1g(n) \le f(n) \le c_2g(n)$  for all  $n \ge n_0$ 
  - So big-theta ( $\theta$ ) gives a tight bound

We usually show algorithms (in code) are  $\theta(g(n))$ . Next class, we'll also discuss how to show **problems** are  $\theta(g(n))$ .

- True or false: 3n+2 is  $O(n^3)$
- True or false: 3n+2 is  $\Theta(n^3)$

Q7b,c, 10

## Big-Oh Style

Give tightest bound you can

- Saying 3*n*+2 is O(*n*<sup>3</sup>) is true, but not as useful as saying it's O(*n*)
- On a test, we'll ask for Θ to be clear.
- Simplify:
  - You could also say: 3n+2 is  $O(5n-3\log(n) + 17)$
  - And it would be technically correct...
  - It would also be poor taste ... and your grade will reflect that.

## Efficiency in context

- There are times when one might choose a higher-order algorithm over a lower-order one.
- Brainstorm some ideas to share with the class

C.A.R. Hoare, inventor of quicksort, wrote: *Premature optimization is the root of all evil.*