## CSCI 136

# Data Structures \& <br> Advanced Programming 

Lecture 9
Fall 2017
Instructors: Bills

## Administrative Details

- Lab 3 Today!
- You may work with a partner
- Come to lab with a plan!
- Try to answer questions before lab


## Last Time

- Note: Storing null values in Lists
- More on Doubly-Linked List
- Lab this week: Doubly Linked Lists with dummy nodes
- Abstract Classes and Inheritance
- Return of the Card Classes!
- The Structure5 Universe to date


## Today

- Measuring Growth
- Big-O
- Introduction to Recursion


## Measuring Computational Cost

Consider these two code fragments...

```
for (int i=0; \(i \quad<a r r . l e n g t h ; ~ i++)\)
```

```
    if (arr[i] == x) return "Found it!";
```

```
    if (arr[i] == x) return "Found it!";
```

...and...

```
for (int i=0; i < arr.length; i++)
    for (int j=0; j < arr.length; j++)
    if( i !=j && arr[i] == arr[j]) return "Match!";
```

How long does it take to execute each block?

## Measuring Computational Cost

- How can we measure the amount of work needed by a computation?
- Absolute clock time
- Problems?
- Different machines have different clocks
- Too much other stuff happening (network, OS, etc)
- Not consistent. Need lots of tests to predict future behavior


## Measuring Computational Cost

- A better way: Counting computations
- Count all computational steps?
- Count how many "expensive" operations were performed?
- Count number of times " $x$ " happens?
- For a specific event or action "x"
- i.e., How many times a certain variable changes
- Question: How accurate do we need to be?
- 64 vs 65 ? 100 vs I05? Does it really matter??


## An Example

```
// Pre: array length n > 0
public static int findPosOfMax(int[] arr) {
    int maxPos = 0 // A wild guess
    for(int i = 1; i < arr.length; i++)
        if (arr[maxPos] < arr[i]) maxPos = i;
```

    return maxPos;
    \}

- Can we count steps exactly?
- "if" makes it hard
- Idea: Overcount: assume "if" block always runs
- Overcounting gives upper bound on run time
- Can also undercount for lower bound
- Overcount: 4(n-I) + 4; undercount: 3(n-I) + 4


## Measuring Computational Cost

- Rather than keeping exact counts, we want to know the order of magnitude of occurrences
- 60 vs 600 vs 6000 , not 65 vs 68
- n , not $4(\mathrm{n}-\mathrm{I})+4$
- We want to make comparisons without looking at details and without running tests
- Avoid using specific numbers or values
- Look for overall trends


## Measuring Computational Cost

- How does algorithm scale with problem size?
- E.g.: If I double the size of the problem instance, how much longer will it take to solve:
- Find maximum: $\mathrm{n}-\mathrm{I} \rightarrow(2 \mathrm{n})-\mathrm{I}$ ( $\approx$ twice as long)
- Bubble sort: $n(n-I) / 2 \rightarrow 2 n(2 n-I) / 2(\approx 4$ times as long)
- Subset sum: $2^{n-1} \rightarrow 2^{2 n-1}$ ( $2^{n}$ times as long!!!)
- Etc.
- We will also measure amount of space used by an algorithm using the same ideas....


## Function Growth

Consider the following functions, for $x \geq 1$

- $f(x)=1$
- $g(x)=\log _{2}(x) / /$ Reminder: if $x=2^{\wedge} n, \log _{2}(x)=n$
- $h(x)=x$
- $m(x)=x \log _{2}(x)$
- $n(x)=x^{2}$
- $p(x)=x^{3}$
- $r(x)=2^{x}$


## Function Growth



## Function Growth \& Big-O

- Rule of thumb: ignore multiplicative constants
- Examples:
- Treat n and $\mathrm{n} / 2$ as same order of magnitude
- $n^{2} / 1000,2 n^{2}$, and $1000 n^{2}$ are "pretty much" just $n^{2}$
- $a_{0} n^{k}+a_{1} n^{k-1}+a_{2} n^{k-2+\ldots} a_{k}$ is roughly $n^{k}$
- The key is to find the most significant or dominant term
- Ex: $\lim _{x \rightarrow \infty}\left(3 x^{4}-10 x^{3}-I\right) / x^{4}=3(W h y ?)$
- So $3 x^{4}-10 x^{3}-1$ grows "like" $x^{4}$


## Asymptotic Bounds (Big-O Analysis)

- A function $f(n)$ is $O(g(n))$ if and only if there exist positive constants $c$ and $n_{0}$ such that

$$
|f(n)| \leq c \cdot g(n) \text { for all } n \geq n_{0}
$$

- g is "at least as big as" ffor large $\mathbf{n}$
- Up to a multaplicative constant c!
- Example:
- $f(n)=n^{2} / 2$ is $O\left(n^{2}\right)$
- $f(n)=1000 n^{3}$ is $O\left(n^{3}\right)$
- $f(n)=n / 2$ is $O(n)$


## Determining "Best" Upper Bounds

- We typically want the smallest upper bound when we estimate running time
- Example: Let $\mathrm{f}(\mathrm{n})=3 \mathrm{n}^{2}$
- $f(n)$ is $O\left(n^{2}\right)$
- $f(n)$ is $O\left(\mathrm{n}^{3}\right)$
- $f(n)$ is $O\left(2^{n}\right)$ (see next slide)
- $f(n)$ is NOT O(n) (!!)
- "Best" upper bound is $\mathrm{O}\left(\mathrm{n}^{2}\right)$
- We care about $\mathbf{c}$ and $\mathbf{n}_{\mathbf{0}}$ in practice, but focus on size of $\mathbf{g}$ when designing algorithms and data structures


## What's $\mathrm{n}_{0}$ ? Messy Functions

- Example: Let $f(n)=3 n^{2}-4 n+1$.
$\mathrm{f}(\mathrm{n})$ is $\mathrm{O}\left(\mathrm{n}^{2}\right)$
- Well, $3 n^{2}-4 n+I \leq 3 n^{2}+I \leq 4 n^{2}$, for $n \geq I$
- So, for $\mathrm{c}=4$ and $\mathrm{n}_{0}=\mathrm{I}$, we satisfy Big-O definition
- Example: Let $f(n)=n^{k}$, for any fixed $k \geq I$. $f(n)$ is $O\left(2^{n}\right)$
- Harder to show: $\mathrm{ls} \mathrm{n}^{\mathrm{k}} \leq \mathrm{c} 2^{\mathrm{n}}$ for some $\mathrm{c}>0$ and large enough n ?
- It is if and only if $\log _{2}\left(n^{k}\right) \leq \log _{2}\left(2^{n}\right)$, that is, iff $k \log _{2}(n) \leq n$.
- That is iff $k \leq n / \log _{2}(n)$. But $n / \log _{2}(n) \rightarrow \infty$ as $n \rightarrow \infty$
- This implies that for some $n_{0}$ on $n / \log _{2}(n) \geq k$ if $n \geq n_{0}$
- Thus $n \geq k \log _{2}(n)$ for $n \geq n_{0}$ and so $2^{n} \geq n^{k}$


## Input-dependent Running Times

- Algorithms may have different running times for different input values
- Best case (typically not useful)
- Sort already sorted array in $O(n)$
- Find item in first place that we look $\mathrm{O}(\mathrm{I})$
- Worst case (generally useful, sometimes misleading)
- Don't find item in list $O(n)$
- Reverse order sort $O\left(n^{2}\right)$
- Average case (useful, but often hard to compute)
- Linear search O(n)
- QuickSort random array $O(n \log n) \leftarrow W e ’ l l$ sort soon


## Vector Operations : Worst-Case

For $\mathrm{n}=$ Vector size (not capacity!):

- $\mathrm{O}(\mathrm{I})$ : size(), capacity(), isEmpty(), get(i), set(i), firstElement(), lastElement()
- O(n): indexOf(), contains(), remove(elt), remove(i)
- What about add methods?
- If Vector doesn't need to grow
- add(elt) is $O(1)$ but add(elt, $i)$ is $O(n)$
- Otherwise, depends on ensureCapacity() time
- Time to compute newLength : $\mathrm{O}\left(\log _{2}(\mathrm{n})\right.$ )
- Time to copy array: O(n)
- $\mathrm{O}\left(\log _{2}(\mathrm{n})\right)+\mathrm{O}(\mathrm{n})$ is $\mathrm{O}(\mathrm{n})$


## Vectors: Add Method Complexity

Suppose we grow the Vector's array by a fixed amount d. How long does it take to add n items to an empty Vector?

- The array will be copied each time its capacity needs to exceed a multiple of $d$
- At sizes 0, d, 2d, ... , n/d.
- Copying an array of size kd takes ckd steps for some constant c , giving a total of

$$
\sum_{k=1}^{n / d} c k d=c d \sum_{k=1}^{n / d} k=c d\left(\frac{n}{d}\right)\left(\frac{n}{d}+1\right) / 2=O\left(n^{2}\right)
$$

## Vectors: Add Method Complexity

Suppose we grow the Vector's array by doubling. How long does it take to add n items to an empty Vector?

- The array will be copied each time its capacity needs to exceed a power of 2
- At sizes $0, I, 2,4,8 \ldots 2^{\log _{2} n}$
- Copying an array of size $2^{k}$ takes c $2^{k}$ steps for some constant c , giving a total of

$$
\sum_{k=1}^{\log _{2} n} c 2^{k}=c \sum_{k=1}^{\log _{2} n} 2^{k}=c\left(2^{\log _{2} n+1}-1\right)=O(n)
$$

- Very cool!

