

# CSE 326: Data Structures

## Topic 2: Asymptotic Analysis

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## Course Policies – Updated

- Written homeworks
  - Due at the start of class on due date
  - No late homeworks accepted
- Programming homeworks
  - Turned in electronically before 11pm on due date
  - Once per quarter: use your “late day” for extra 24 hours – **Must email TA**
- Work in teams only on explicit team projects
  - Appropriate *discussions* encouraged – see website
- Approximate Grading
  - Weekly assignments: 35%
  - Midterm: 20% **Friday July 25, in class**
  - Final: 30% **Friday Aug. 22 in class**
  - **Best of above 3:** 10%
  - Participation: 5%

## Analysis of Algorithms

- Efficiency measure
  - how long the program runs **time complexity**
  - how much memory it uses **space complexity**
    - For today, we'll focus on time complexity only
- *Why analyze at all?*
  - Confidence: algorithm will work well in practice
  - Insight : alternative, better algorithms

## Asymptotic Analysis

- Complexity as a function of input size  $n$ 
  - $T(n) = 4n + 5$
  - $T(n) = 0.5 n \log n - 2n + 7$
  - $T(n) = 2^n + n^3 + 3n$
- *What happens as  $n$  grows?*

## Why do we care?

- Most algorithms are fast for small  $n$ 
  - Time difference too small to be noticeable
  - External things dominate (OS, disk I/O, ...)
- BUT  $n$  is often large in practice
  - Databases, internet, graphics, ...
- Time difference really shows up as  $n$  grows!

## Luke Takes a Break

2	3	5	16	37	50	73	75	126
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```
bool ArrayFind (int array[],
               int n,
               int key )
{
    // Insert your algorithm here
```

*What algorithm would you choose  
to implement this code snippet?*

## Luke Takes a Break: Simplifying assumptions

- Ideal single-processor machine (serialized operations)
- “Standard” instruction set (load, add, store, etc.)
- All operations take 1 time unit (including, for our purposes, each Java or C++ statement)

## LTaB: Analyzing Code

Basic Java/C++ operations	Constant time
Consecutive statements	Sum of times
Conditionals	Larger branch plus test
Loops	Sum of iterations
Function calls	Cost of function body
Recursive functions	Solve recurrence relation

## LTaB: Linear Search Analysis

```
bool ArrayFind( int array[],
               int n,
               int key )
{
    for( int i = 0; i < n; i++ )
    {
        // Found it!
        if( array[i] == key )
            return true;
    }
    return false;
}
```

• Best Case:

• Worst Case:

## LTaB: Binary Search Analysis

```
bool ArrayFind( int array[], int s,
               int e, int key ) {
    // The subarray is empty
    if( s > e )
        return false;

    // Search this subarray
    int mid = ( e + s ) / 2;
    if( array[key] == array[mid] ) {
        return true;
    } else if( key < array[mid] ) {
        return ArrayFind( array, s,
                           mid-1, key );
    } else {
        return ArrayFind( array, mid+1,
                           e, key );
    }
}
```

• Best case:

• Worst case:

## Back to work: Solving Recurrence Relations

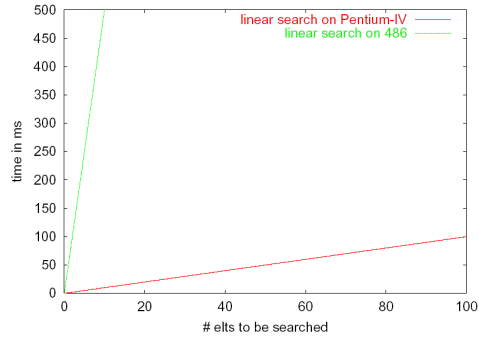
1. Determine the recurrence relation. What are the base case(s)?
2. “Expand” the original relation to find an equivalent general expression *in terms of the number of expansions*.
3. Find a closed-form expression by setting *the number of expansions* to a value which reduces the problem to a base case

## Linear Search vs Binary Search

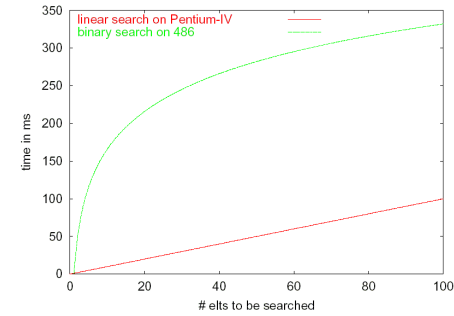
	Linear Search	Binary Search
Best Case		
Worst Case		

*So ... which algorithm is best?  
What tradeoffs did you make?*

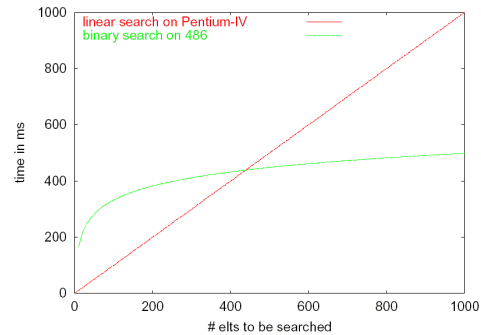
## Fast Computer vs. Slow Computer



## Fast Computer vs. Smart Programmer (round 1)



## Fast Computer vs. Smart Programmer (round 2)



## Asymptotic Analysis

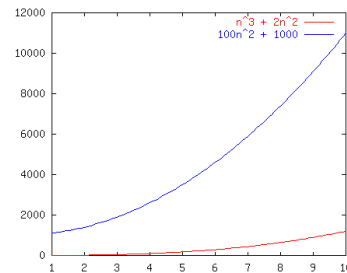
- Asymptotic analysis looks at the *order* of the running time of the algorithm
  - A valuable tool when the input gets “large”
  - Ignores the *effects of different machines* or *different implementations* of the same algorithm
- Intuitively, to find the asymptotic runtime, throw away the constants and low-order terms
  - Linear search is  $T(n) = 2n + 1$  ?  $O(n)$
  - Binary search is  $T(n) = 4 \log_2 n + 2$  ?  $O(\log n)$

*Remember: the fastest algorithm has the slowest growing function for its runtime*

## Order Notation: Intuition

$$f(n) = n^3 + 2n^2$$

$$g(n) = 100n^2 + 1000$$



Although not yet apparent, as  $n$  gets “sufficiently large”,  $f(n)$  will be “greater than or equal to”  $g(n)$

## Order Notation: Definition

$O(f(n))$  is a set of functions

$g(n) \in O(f(n))$  iff  
There exist  $c$  and  $n_0$  such that  $g(n) \leq c f(n)$  for all  $n \geq n_0$

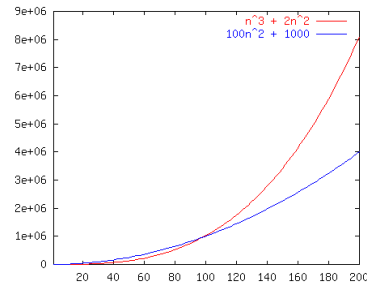
Example:

$$100n^2 + 1000 \in O(n^3 + 2n^2) \text{ for all } n \geq 19$$

$$\text{So } g(n) \in O(f(n))$$

Sometimes, you’ll see the notation  $g(n) = O(f(n))$ . This equivalent to  $g(n) \in O(f(n))$ . However, the notation  $O(f(n)) = g(n)$  is *not* correct

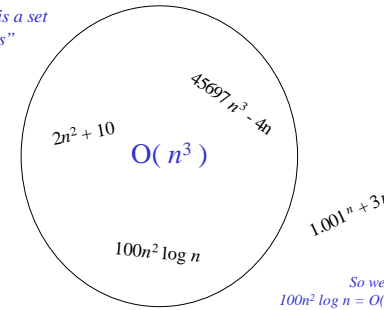
## Order Notation: Example



$100n^2 + 1000 \stackrel{?}{=} 5(n^3 + 2n^2)$  for all  $n \geq 19$   
 So  $g(n) \stackrel{?}{=} O(f(n))$

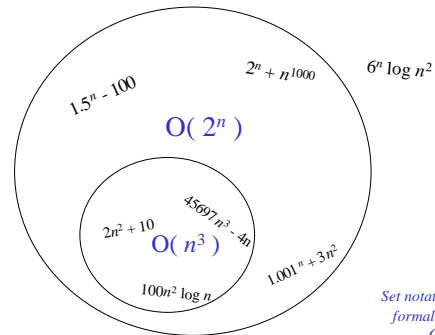
## Oops: Set Notation

" $O(f(n))$  is a set of functions"



So we say both  
 $100n^2 \log n = O(n^3)$  and  
 $100n^2 \log n \neq O(n^2)$

## Set Notation



Set notation allows us to formalize our intuition  
 $O(n^3) \stackrel{?}{=} O(2^n)$

## Big-O Common Names

- constant:  $O(1)$
- logarithmic:  $O(\log n)$  ( $\log_k n, \log n^2 \stackrel{?}{=} O(\log n)$ )
- poly-log:  $O(\log^k n)$
- linear:  $O(n)$
- log-linear:  $O(n \log n)$
- superlinear:  $O(n^{1+c})$  ( $c$  is a constant  $> 0$ )
- quadratic:  $O(n^2)$
- cubic:  $O(n^3)$
- polynomial:  $O(n^k)$  ( $k$  is a constant)
- exponential:  $O(c^n)$  ( $c$  is a constant  $> 1$ )

## Meet the Family

- $O(f(n))$  is the set of all functions asymptotically less than or equal to  $f(n)$ 
  - $o(f(n))$  is the set of all functions asymptotically strictly less than  $f(n)$
- $\Omega(f(n))$  is the set of all functions asymptotically greater than or equal to  $f(n)$ 
  - $\omega(f(n))$  is the set of all functions asymptotically strictly greater than  $f(n)$
- $\Theta(f(n))$  is the set of all functions asymptotically equal to  $f(n)$

## Meet the Family Formally (don't worry about dressing up)

- $g(n) \stackrel{?}{=} O(f(n))$  iff  
 There exist  $c$  and  $n_0$  such that  $g(n) \leq c f(n)$  for all  $n \geq n_0$ 
  - $g(n) \stackrel{?}{=} o(f(n))$  iff  
 There exists a  $n_0$  such that  $g(n) < c f(n)$  for all  $c$  and  $n \geq n_0$
- $g(n) \stackrel{?}{=} \Omega(f(n))$  iff  
 There exist  $c$  and  $n_0$  such that  $g(n) \geq c f(n)$  for all  $n \geq n_0$ 
  - $g(n) \stackrel{?}{=} \omega(f(n))$  iff  
 There exists a  $n_0$  such that  $g(n) > c f(n)$  for all  $c$  and  $n \geq n_0$
- $g(n) \stackrel{?}{=} \Theta(f(n))$  iff  
 $g(n) \stackrel{?}{=} O(f(n))$  and  $g(n) \stackrel{?}{=} \Omega(f(n))$

## Big-Omega et al. Intuitively

Asymptotic Notation	Mathematics Relation
O	?
?	?
?	=
o	<
?	>

## True or False?

$10,000 n^2 + 25n$	? $(n^2)$	
$10^{-10} n^2$	? $(n^2)$	
$n^3 + 4$	? $(n^3)$	
$n \log n$	? $O(2^n)$	
$n \log n$	? $(n^2)$	
$n^3 + 4$	? $o(n^4)$	

## Types of Analysis

Two orthogonal axes:

- **bound flavor**
  - upper bound (O, o)
  - lower bound (?, ?)
  - asymptotically tight (?)
- **analysis case**
  - worst case (adversary)
  - average case
  - best case
  - "amortized"

## LTaB: Pros and Cons of Asymptotic Analysis

## Proof by...

- Counterexample
  - show an example which does not fit with the theorem
  - QED (the theorem is disproven)
- Contradiction
  - assume the opposite of the theorem
  - derive a contradiction
  - QED (the theorem is proven)
- Induction
  - prove for a base case (e.g.,  $n = 1$ )
  - assume for an anonymous value ( $n$ )
  - prove for the next value ( $n + 1$ )
  - QED

## Inductive Proof of Correctness

```
int sum(int v[], int n)
{
    if (n==0) return 0;
    else return v[n-1]+sum(v,n-1);
}
```

**Theorem:**  $\text{sum}(v,n)$  correctly returns sum of 1<sup>st</sup>  $n$  elements of array  $v$  for any  $n$ .

**Basis Step:** Program is correct for  $n=0$ ; returns 0.  $\checkmark$

**Inductive Hypothesis** ( $n=k$ ): Assume  $\text{sum}(v,k)$  returns sum of first  $k$  elements of  $v$ .

**Inductive Step** ( $n=k+1$ ):  $\text{sum}(v,k+1)$  returns  $v[k]+\text{sum}(v,k)$ , which is the same of the first  $k+1$  elements of  $v$ .  $\checkmark$

## Inductive Proof (Binary Search)

If you know the closed form solution,  
you can validate it by ordinary induction

$T(1) \leq b \leq c \log 1 \leq b$  base case

Assume  $T(n) \leq b \leq c \log n$  hypothesis

$T(2n) \leq T(n) \leq c$  definition of  $T(n)$

$T(2n) \leq (b \leq c \log n) \leq c$  by induction hypothesis

$T(2n) \leq b \leq c((\log n) \leq 1)$

$T(2n) \leq b \leq c((\log n) \leq (\log 2))$

$T(2n) \leq b \leq c \log(2n)$  Q.E.D.

Thus:  $T(n) \leq c \log n$

## Asymptotic Analysis Summary

- Determine what characterizes a problem's size
- Express how much resources (time, memory, etc.) an algorithm requires as a function of input size using  $O(\bullet)$ ,  $\Theta(\bullet)$ ,  $\Omega(\bullet)$ 
  - worst case
  - best case
  - average case
  - common case
  - overall

## To Do

- Continue Homework 1
  - Due Monday, June 30 at 11 PM sharp!
  - Bring questions to section tomorrow
- Sign up for 326 mailing list(s)
- Continue reading 1.1-1.3, Chapters 2 and 3 in the book
  - Also start/skim on next sections: 4.1 (introduction to trees), and sections 6.1-6.4 (priority queues and binary heaps)