



# Lecture 3: How to measure efficiency

Data Structures and  
Algorithms

CSE 373 SU 18 – BEN JONES

1

# Announcements

- Course background survey due by Friday
- HW 1 is Due Friday
- Alex has Office Hours after class (2:30-4:30) CSE 006, will help with setup
  - If you have any questions about your setup please come to office hours so we can iron out all the wrinkles before the partnered projects begin next week.
- HW 2 Assigned on Friday – Partner selection forms due by 11:59pm **Thursday**  
<https://goo.gl/forms/rVrVUKFDdsqI8pkD2>

## Review: Sequential Search

**sequential search:** Locates a target value in an array / list by examining each element from start to finish.

- How many elements will it need to examine?
- Example: Searching the array below for the value **42**:

index	0	1	2	3	4	5	6	7	8	9	<b>10</b>	11	12	13	14	15	16
value	-4	2	7	10	15	20	22	25	30	36	<b>42</b>	50	56	68	85	92	103

i

- What is the best case?
- What is the worst case?
- What is the complexity class?

## Review: Binary Search

**binary search:** Locates a target value in a *sorted* array or list by successively eliminating half of the array from consideration.

- How many elements will it need to examine?
- Example: Searching the array below for the value **42**:

index	0	1	2	3	4	5	6	7	8	9	<b>10</b>	11	12	13	14	15	16
value	-4	2	7	10	15	20	22	25	30	36	<b>42</b>	50	56	68	85	92	103

↑  
min

↑  
mid

↑  
max

- What is the best case?
- What is the worst case?
- What is the complexity class?

# Analyzing Binary Search

What is the pattern?

- At each iteration, we eliminate half of the remaining elements

How long does it take to finish?

- 1<sup>st</sup> iteration –  $N/2$  elements remain
- 2<sup>nd</sup> iteration –  $N/4$  elements remain
- Kth iteration –  $N/2^k$  elements remain
- Done when  $N/2^k = 1$

index	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
value	-4	2	7	10	15	20	22	25	30	36	42	50	56	68	85	92	103

# Analyzing Binary Search

$$\frac{N}{2^k} = 1$$
$$N = 2^k$$
$$\log_2 N = \log_2 N$$

$$\Rightarrow O(\log n)$$

↑ We lost the base!  
This will be explained later.

Review: logarithms

$\log_b a = x$  means  
that  $x$  solves the problem

$b^x = a$ . This means  
that

$$\log (b^x) = x$$

asks  $b$  for  $x$  to solve

$$b^x = b^x, \text{ so } x = x.$$

# Analyzing Binary Search

Finishes when  $N / 2^K = 1$

$$N / 2^K = 1$$

-> multiply right side by  $2^K$

$$N = 2^K$$

-> isolate K exponent with logarithm

$$\log_2 N = k$$

Is this exact?

- N can be things other than powers of 2
- If N is odd we can't technically use  $\log_2$
- When we have an odd number of elements we select the larger half
- Within a fair rounding error

# Asymptotic Analysis

**asymptotic analysis:** how the runtime of an algorithm grows as the data set grows

## Approximations / Rules

- Basic operations take "constant" time
  - Assigning a variable
  - Accessing a field or array index
- Consecutive statements
  - Sum of time for each statement
- Function calls
  - Time of function's body
- Conditionals
  - Time of condition + maximum time of branch code
- Loops
  - Number of iterations x time for loop body



# Modeling Case Study

**Goal:** return 'true' if a sorted array of ints contains duplicates

**Solution 1:** compare each pair of elements

```
public boolean hasDuplicate1(int[] array) {
    for (int i = 0; i < array.length; i++) {
        for (int j = 0; j < array.length; j++) {
            if (i != j && array[i] == array[j]) {
                return true;
            }
        }
    }
    return false;
}
```

**Solution 2:** compare each consecutive pair of elements

```
public boolean hasDuplicate2(int[] array) {
    for (int i = 0; i < array.length - 1; i++) {
        if (array[i] == array[i + 1]) {
            return true;
        }
    }
    return false;
}
```

## Modeling Case Study: Solution 2

$T(n)$  where  $n = \text{array.length}$

-> work inside out

**Solution 2:** compare each consecutive pair of elements

```
public boolean hasDuplicate2(int[] array) {  
    for (int i = 0; i < array.length - 1; i++) {  
        if (array[i] == array[i + 1]) { +4  
            return true; +1  
        }  
    }  
    return false; +1  
}
```

If statement = 5 }  $\times n - 1$

} +1

$$T(n) = 5(n-1) + 1$$

linear time complexity class  $O(n)$

## Modeling Case Study: Solution 1

**Solution 1:** compare each consecutive pair of elements

```
public boolean hasDuplicate1(int[] array) {  
    for (int i = 0; i < array.length; i++) { x n  
        for (int j = 0; j < array.length; j++) { x n  
            if (i != j && array[i] == array[j]) { +5 }  
            return true; +1  
        }  
    }  
    return false; +1  
}
```

The diagram illustrates the complexity analysis of the code. It shows three nested levels of complexity: the innermost loop body (if statement and return) is labeled **+5**; the inner loop (for j) is labeled **6**; and the outer loop (for i) is labeled **6n**. The total complexity is indicated as **6n<sup>2</sup>**.

$$T(n) = 6n^2 + 1$$

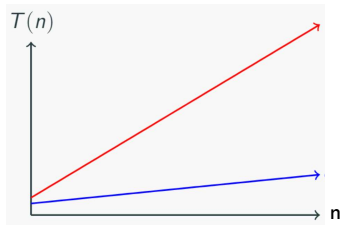
quadratic time complexity class  $O(n^2)$



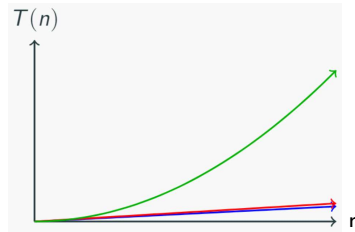
## Comparing Functions

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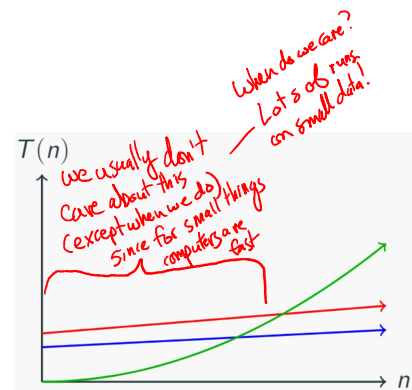
# Function growth



$n$  and  $4n$  look very different up close



$n$  and  $4n$  look the same over time  
 $n^2$  eventually dominates  $n$



$n^2$  doesn't start off dominating the linear functions  
It eventually takes over...

## Function comparison: exercise

$f(n) = n \leq g(n) = 5n + 3$ ? **True** – all linear functions are treated as equivalent

$f(n) = 5n + 3 \leq g(n) = n$ ? **True**

$f(n) = 5n + 3 \leq g(n) = 1$ ? **False**

$f(n) = 5n + 3 \leq g(n) = n^2$ ? **True** – quadratic will always dominate linear

$f(n) = n^2 + 3n + 2 \leq g(n) = n^3$ ? **True**

$f(n) = n^3 \leq g(n) = n^2 + 3n + 2$ ? **False**

## Definition: function domination

### Definition: Domination

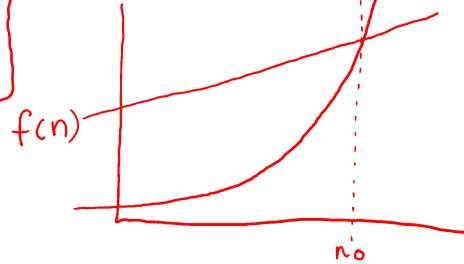
A function  $f(n)$  is **dominated** by  $g(n)$  when...

There exists two constants  $c > 0$  and  $n_0 > 0$

Such that for all values of  $n \geq n_0$

$$f(n) \leq c \cdot g(n)$$

i.e.  $g(n)$  is eventually always  
bigger than  $f(n)$ :  
(up to a constant factor)  $c \cdot g(n)$



Example:

Is  $f(n) = n$  dominated by  $g(n) = 5n + 3$ ?

$$c = 1$$

$$n_0 = 1$$

Yes!

## Exercise: Function Domination

Demonstrate that  $5n^2 + 3n + 6$  is dominated by  $n^3$  by finding a  $c$  and  $n_0$  that satisfy the definition of domination

$$5n^2 + 3n + 6 \leq 5n^2 + 3n^2 + 6n^2 \text{ when } n \geq 1$$

$$5n^2 + 3n^2 + 6n^2 = 14n^2$$

$$5n^2 + 3n + 6 \leq 14n^2 \text{ for } n \geq 1$$

$$14n^2 \leq c \cdot n^3 \text{ for } c = ? \text{ } n \geq ?$$

$$\frac{14}{n} \rightarrow c = 14 \text{ \& } n \geq 1$$

Is there a <sup>(smaller)</sup> tighter upper bound?  
Yes!  $n^2$ , use  $c=6$

The "smallest"  $g(n)$  such that  $f(n) \in O(g(n))$  is a tight bound!



## Definition: Big O

If  $f(n) = n \leq g(n) = 5n + 3 \leq h(n) = 100n$  and

$h(n) = 100n \leq g(n) = 5n + 3 \leq f(n)$   $n$

Really they are all the "same"

(for measuring upper bounds)  
often worst case  
(but this is a general mathematical categorization of functions)

Definition: Big O

$O(f(n))$  is the "family" or "set" of all functions that are dominated by  $f(n)$

Question: are  $O(n)$ ,  $O(5n + 3)$  and  $O(100n)$  all the same?

True! By convention we pick simplest of the above  $\rightarrow O(n)$  ie "linear"

## Definitions: Big $\Omega$

"f(n) is greater than or equal to g(n)"

F(n) dominates g(n) when:

There exists two constants such that  $c > 0$  and  $n_0 > 0$

Such that for all values  $n \geq n_0$

$F(n) \geq c * g(n)$  is true

Definition: Big  $\Omega$

$\Omega(f(n))$  is the family of all functions that dominates f(n)

## ∈ Element Of

$f(n)$  is dominated by  $g(n)$

Is that the same as

" $f(n)$  is contained inside  $O(g(n))$ "

Yes!

$f(n) \in g(n)$

# Examples

$4n^2 \in \Omega(1)$

true

$4n^2 \in \Omega(n)$

true

$4n^2 \in \Omega(n^2)$

true

$4n^2 \in \Omega(n^3)$

false

$4n^2 \in \Omega(n^4)$

false

$4n^2 \in O(1)$

false

$4n^2 \in O(n)$

false

$4n^2 \in O(n^2)$

true

$4n^2 \in O(n^3)$

true

$4n^2 \in O(n^4)$

true

Definition: Big  $O$

$O(f(n))$  is the "family" or "set" of all functions that are dominated by  $f(n)$

Definition: Big  $\Omega$

$\Omega(f(n))$  is the family of all functions that dominates  $f(n)$

## Definitions: Big $\Theta$

We say  $f(n) \in \Theta(g(n))$  when both  
 $f(n) \in O(g(n))$  and  $f(n) \in \Omega(g(n))$  are true  
Which is only when  $f(n) = g(n)$

Definition: Big  $\Theta$

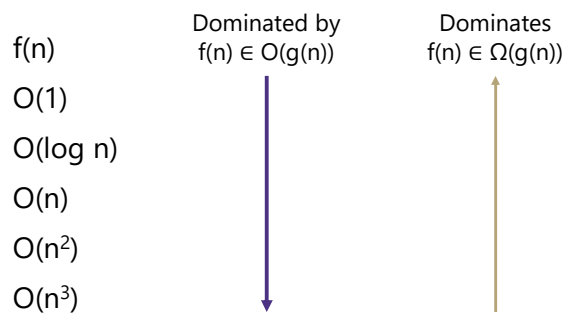
$\Theta(f(n))$  is the family of functions that are equivalent to  $f(n)$

*These are the  
"tight" bounds -  
the function is "squeezed"  
on both sides.*

Industry uses "Big  $\Theta$ " and "Big  $O$ " interchangeably

# Summary

$$O(f(n)) \leq f(n) == \Theta(f(n)) \leq \Omega(f(n))$$



# Justifying the "Rules"

## Approximations / Rules

- Basic operations take "constant" time
  - Assigning a variable
  - Accessing a field or array index
- Consecutive statements
  - Sum of time for each statement
- Function calls
  - Time of function's body
- Conditionals
  - Time of condition + maximum time of branch code
- Loops
  - Number of iterations x time for loop body

upper bound, so take largest constant.

Some finite # of statements, take largest, mult. by # of stmts

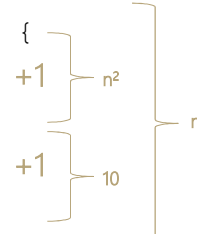
overhead of a fn call is const, so dominated by fn running time

worst case: similar to all ops taking the same time

All of these rules are, up to a constant, upper-bound approximations  
(they only can increase your estimate, so you definitely have an upper bound.)

## A Slightly Harder example

```
public void mystery(int n) {  
    for (int i = 0; i < n; i++) {  
        for (int j = 0; j < n * n; j++) {  
            System.out.println("Hello");  
        }  
        for (int j = 0; j < 10; j++) {  
            System.out.println("world");  
        }  
    }  
}
```



The diagram illustrates the complexity of the nested loops. The first loop runs  $n$  times. Inside it, there are two nested loops. The first nested loop runs  $n^2$  times, and the second nested loop runs  $10$  times. The total complexity is  $n \cdot (n^2 + 10)$ .

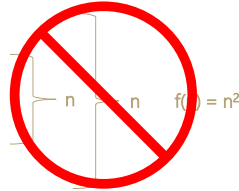
*Remember:* work outside in

Solution:  $T(n) = n(n^2 + 10) = n^3 + 10n$



## Modeling Complex Loops

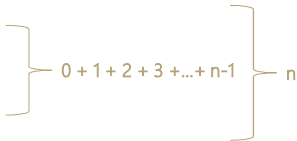
```
for (int i = 0; i < n; i++) {  
    for (int j = 0; j < i; j++) {  
        System.out.println("Hello!");  
    }  
}
```



Keep an eye on loop bounds!

# Modeling Complex Loops

```
for (int i = 0; i < n; i++) {  
    for (int j = 0; j < i; j++) {  
        System.out.println("Hello!"); +c  
    }  
}
```



Summation

$$1 + 2 + 3 + 4 + \dots + n = \sum_{i=1}^n i$$

Definition: Summation

$$\sum_{i=a}^b f(i) = f(a) + f(a+1) + f(a+2) + \dots + f(b-2) + f(b-1) + f(b)$$

$$T(n) = \sum_{i=0}^{n-1} \sum_{j=0}^{i-1} c$$

# Simplifying Summations

```
for (int i = 0; i < n; i++) {
    for (int j = 0; j < i; j++) {
        System.out.println("Hello!"); +c
    }
}
```

$\left. \begin{array}{c} \text{ } \end{array} \right\} 0 + 1 + 2 + 3 + \dots + n-1 \left. \begin{array}{c} \text{ } \end{array} \right\} n \rightarrow \begin{array}{l} (0c + 1c + 2c + 3c + \dots + i-1c) \\ + (0c + 1c + 2c + 3c + \dots + i-1c) \\ + (0c + 1c + 2c + 3c + \dots + i-1c) \\ + \text{repeat } n \text{ times} \end{array}$

$$T(n) = \sum_{i=0}^{n-1} \sum_{j=0}^{i-1} c = \sum_{i=0}^{n-1} ci \quad \text{Summation of a constant}$$

$$= c \sum_{i=0}^{n-1} i \quad \text{Factoring out a constant}$$

$$= c \frac{n(n-1)}{2} \quad \text{Gauss's Identity}$$

$$= \frac{c}{2}n^2 - \frac{c}{2}n \quad O(n^2)$$

## Function Modeling: Recursion

```
public int factorial(int n) {  
    if (n == 0 || n == 1) { +3 } +c  
        return 1; +1  
    } else {  
        return n * factorial(n - 1); +????  
    }  
}
```

# Function Modeling: Recursion

```
public int factorial(int n) {  
    if (n == 0 || n == 1) {  
        return 1; } else {  
        return n * factorial(n - 1);  
    }  
}
```

$+C_1$  (for the if/else block)  
 $+C_2$  (for the return statement)  
 $+T(n-1)$  (for the recursive call)

$$T(n) = \begin{cases} C_1 & \text{when } n = 0 \text{ or } 1 \\ C_2 + T(n-1) & \text{otherwise} \end{cases}$$

Definition: Recurrence

Mathematical equivalent of an if/else statement  
 $f(n) =$

## Unfolding Method

$$T(n) = \begin{cases} C_1 & \text{when } n = 0 \text{ or } 1 \\ C_2 + T(n-1) & \text{otherwise} \end{cases}$$

$$T(3) = C_2 + T(3-1) = C_2 + (C_2 + T(2-1)) = C_2 + (C_2 + (C_1)) = 2C_2 + C_1$$

$$T(n) = C_1 + \sum_{i=0}^{n-1} C_2$$

Summation of a constant

$$T(n) = C_1 + (n-1)C_2$$