

Algorithmic Analysis

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Objectives

- Introduction to Algorithmic Analysis
- Big-O Notation Formally Defined
- From Source Code to Big-O Notation
- Analysis of Recursive Algorithms

A Graphical Introduction /1

- It's all about **scale**
 - How fast/slow does your algorithm perform with more complex/larger cases?
- **Example:** asking the class a question

$O(1)$

$O(n)$

$O(n^2)$

Get 1 answer

Get everyone's answer

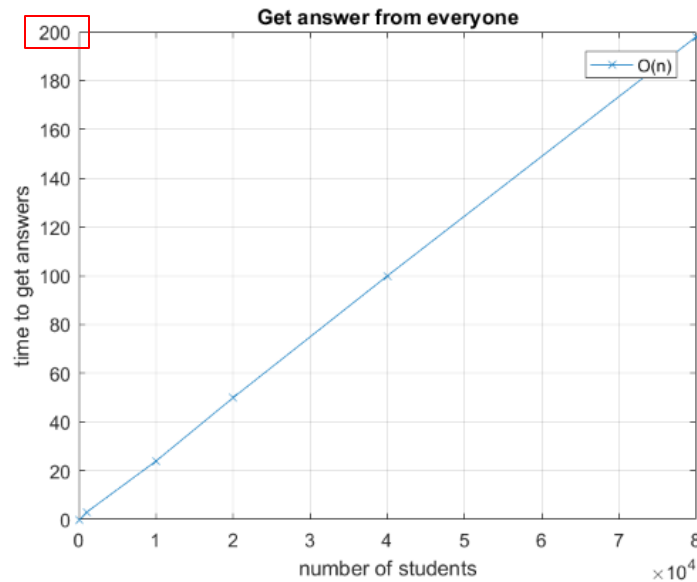
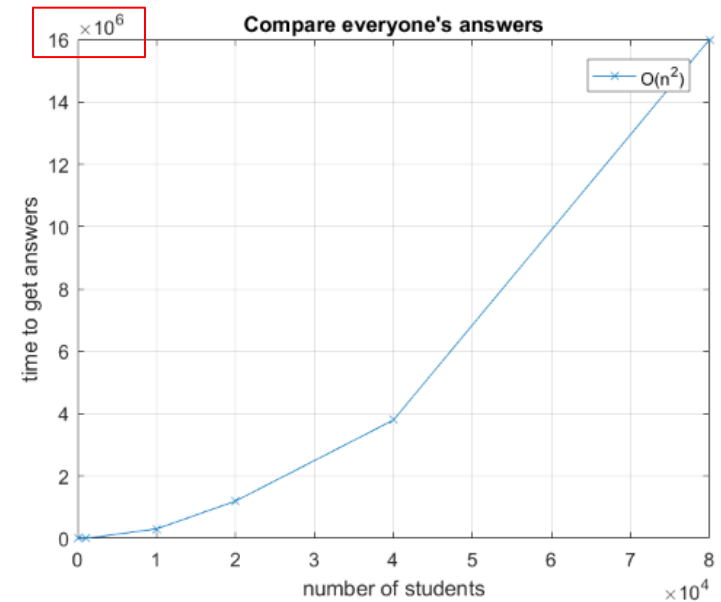
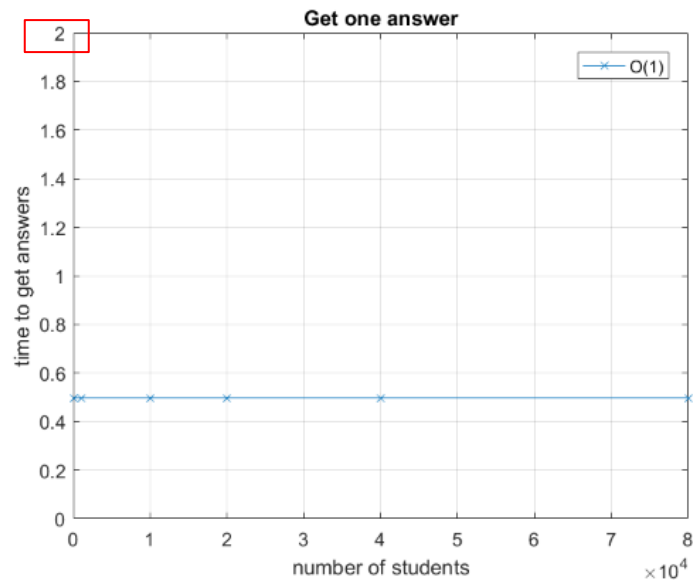
Compare everyone's
answer to everyone else

- Let's start with an interactive example with code

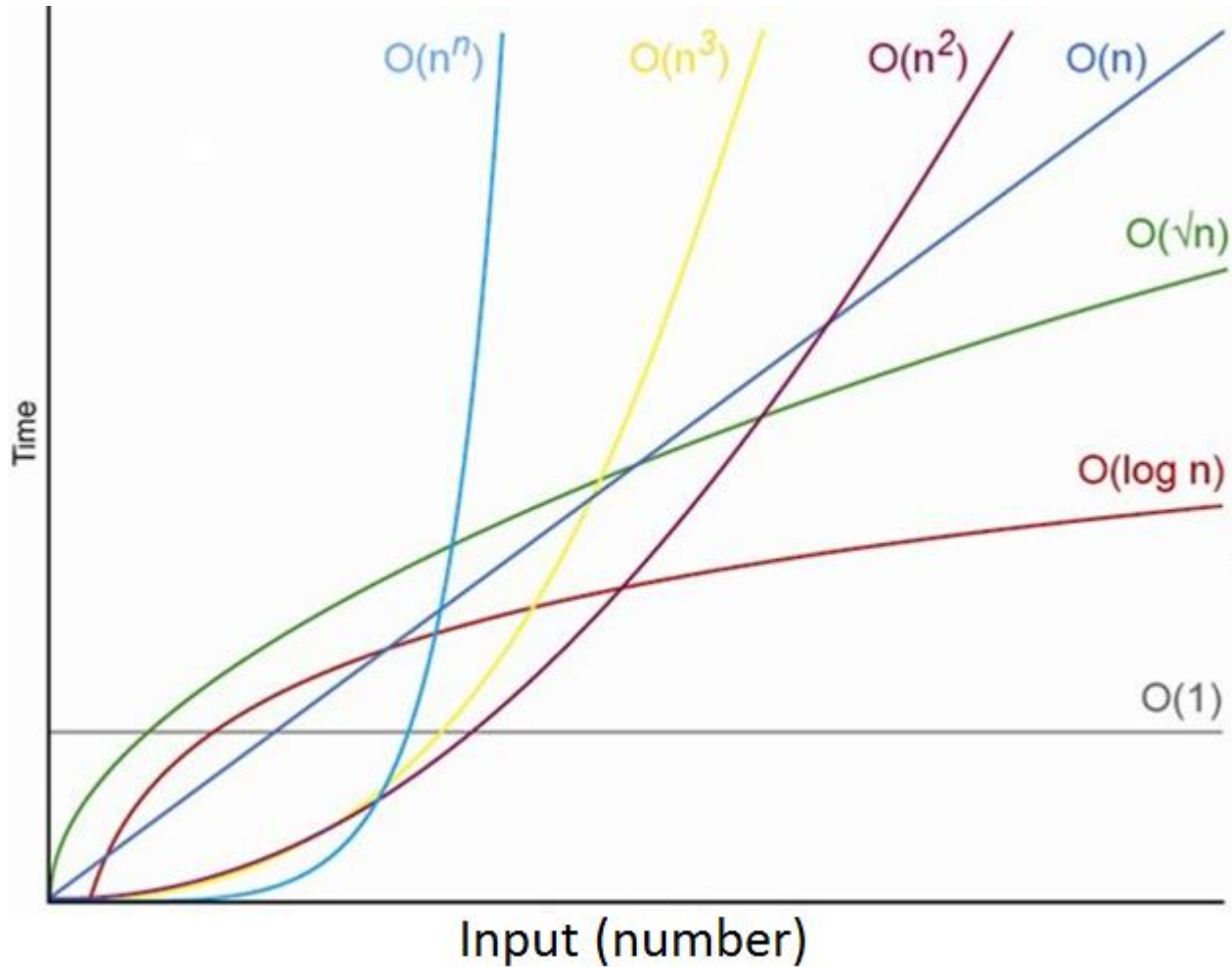


(Empty slide for notes on demo code)

A Graphical Introduction /2



A Graphical Introduction /3



Introduction to Algorithmic Analysis /1

- **The process of measuring performance of a computer program can be challenging**
 - The performance may be affected by the algorithm, compiler, programming language, and machine architecture, all of which play a part in program execution
 - Instead of analyzing the entire execution process, we will focus on classifying only the algorithm and the number of operations that the algorithm performs
 - Moreover, we will attempt to calculate the efficiency of an algorithm before writing any code to save time and cost



Introduction to Algorithmic Analysis /2

- **Our first goal is a method by which we can formally compare two algorithms regardless of the input size**
 - To that end, we will express the number of steps an algorithm takes to run itself to completion (i.e., the number of steps taken) as a function $f(n)$; in $f(n)$, n is the size of the input
 - For each function/algorithm, we will aim to compute $f(n)$ and then compare that measurements against equivalent measurements for other functions/algorithms

Introduction to Algorithmic Analysis /3

■ Searching algorithms:

- For the **SequentialSearch** function given below, the size of the input (**n**) is the size of the array (**n = size**)
- In the best case scenario, the first element of the array is equal to **K**, and the function takes a handful of operations
- In the worst case scenario, the array does not contain **K**, and the function takes at least **n** number of operations

```
int SequentialSearch(int A[], int size, int K) {  
    for (int i = 0; i < size; i++) {  
        if (A[i] == K)  
            return i;  
    }  
    return -1;  
}
```

Introduction to Algorithmic Analysis /4

- **Another method that can be used to perform the search is the binary search that is shown below**
 - In the best case scenario, the middle element of the array is equal to K, and the function takes several operations
 - In the worst case scenario, the array does not contain K, but the function takes less than n number of operations

```
int BinarySearch(int A[], int L, int R, int K) {  
    // A must be already sorted for this to work  
    int mid = (L + R) / 2;  
    if (R < L)  
        return -1;  
    else if (A[mid] == K)  
        return mid;  
    else if (K > A[mid])  
        return BinarySearch(A, mid + 1, R, K);  
    else  
        return BinarySearch(A, L, mid - 1, K);  
}
```

Introduction to Algorithmic Analysis /5

- **So which of the two search functions is faster when given a sorted array as input?**
 - In the best scenarios, both of them take a handful of operations, so both of them perform roughly the same
 - However, what if we are not dealing with the best case?
- **What we are interested in is the increase in the number of operations as the input size grows**
 - For small inputs, both search algorithms may finish in negligible amount of time
 - As the input size grows, so does the time it takes for each algorithm to complete
 - The growth rate of an algorithm will determine which algorithm performs faster for large input sizes

Introduction to Algorithmic Analysis /6

- **To compare the growth of two algorithms, we will consider the worst-case scenario for each algorithm**
 - For the two search algorithms, **SequentialSearch** will take roughly n operations to complete if K is not found
 - At the same time, **BinarySearch** will take less than n operations, and more specifically around $\log(n)$ operations, to complete if K is not found
- **We will express the performance of an algorithm by assigning it to its own class/category**
 - We will use something called Big-O notation to express performance information about an algorithm
 - Using the Big-O notation, **SequentialSearch** can be classified as $O(n)$ and **BinarySearch** as $O(\log(n))$

Introduction to Algorithmic Analysis /7

- There are several common classes of algorithms based on the Big-O notation:

- $O(1)$ - constant time algorithms
- $O(\log(n))$ - logarithmic time algorithms
- $O(n)$ - linear time algorithms
- $O(n \times \log(n))$
- $O(n^2)$ - quadratic time algorithms
- $O(n^3)$ - cubic time algorithms
- $O(2^n)$ - exponential time algorithms
- $O(10^n)$
- $O(n!)$ - factorial time algorithms



Increasing order
of growth

Introduction to Algorithmic Analysis /8

- **Using the Big-O classification, we can compare and group algorithms based on their performance**
 - Out of the two searching algorithms, the binary search, which is an $O(\log(n))$ algorithm, performs faster than the linear search, which is an $O(n)$ algorithm
 - For sorting, $O(n \times \log(n))$ algorithms are the best performing when it comes to comparison-based sorting
 - Exponential algorithms, such as $O(2^n)$, appear in certain classes of problems (e.g., graph problems)
 - However, exponential algorithms are impractical for very large inputs since they could take a very long time to run
 - There are reasonable algorithms that could run “from now until the end of time” and still not complete their function ☺

Big-O Notation Formally Defined /1

- **Big-O notation describes the worst case runtime of a given algorithm**
 - More specifically, Big-O describes the absolute worst case in terms of the number of operations that could occur when running an algorithm against input of size n
- **Formally, for a function $f(n)$ that represents the number of operations for an algorithm:**
 - A function $f(n)$ is classified as $O(g(n))$ if there exist two positive constants K and n_0 such that
$$|f(n)| \leq K|g(n)| \text{ for all } n \geq n_0$$
 - Visually, there exists a positive constant K for which $K|g(n)|$ lies above $f(n)$ for all $n \geq n_0$

Big-O Notation Formally Defined /2

- **Visual demonstration of Big-O notation:**
 - Let $f(x) = x$, $g(x) = x^2$, and $h(x) = \log(x)$
 - Then, $f(x) = O(g(x))$ since $g(x)$ lies above $f(x)$
 - Similarly, $h(x) = O(g(x))$ and $h(x) = O(f(x))$



Source: <https://www.desmos.com/calculator>

Big-O Notation Formally Defined /3

- **Simplification rules regarding Big-O notation:**
 - All logarithmic functions regardless of their base belong to the same $O(\log(n))$ logarithmic class of algorithms
 - All polynomial functions (e.g., $ax^2 + bx + c$) where k is the largest degree belong to the same $O(n^k)$ class
 - Constant terms and multipliers can be ignored when simplifying the expressions (e.g., $O(2 \times n^2) = O(n^2)$)
 - Constant terms are important if we are trying to compare the exact number of operations between two algorithms
 - Exponential functions belong to different classes depending on their base (e.g., $O(2^n)$ & $O(3^n)$ are distinct)

Big-O Notation Formally Defined /4

■ Example1:

■ Let $f(n) = 100n^2$ and $g(n) = n^2$. Show that $f(n) = O(g(n))$

■ Steps:

□ Select $n_0 = 1$, so then for $n \geq n_0$

$$100n^2 \leq K * n^2$$

$$100 \leq K$$

□ Hence, for $K \geq 100$ and $n \geq 1$, $f(n) = O(g(n))$

Big-O Notation Formally Defined /5

■ Example2:

■ Let $f(n) = n^2$ and $g(n) = n^3$. Show that $f(n) = O(g(n))$

■ Steps:

□ Select $n_0 = 1$, so then for $n \geq n_0$

$$n^2 \leq K * n^3$$

$$1 \leq K n$$

$$\frac{1}{K} \leq n$$

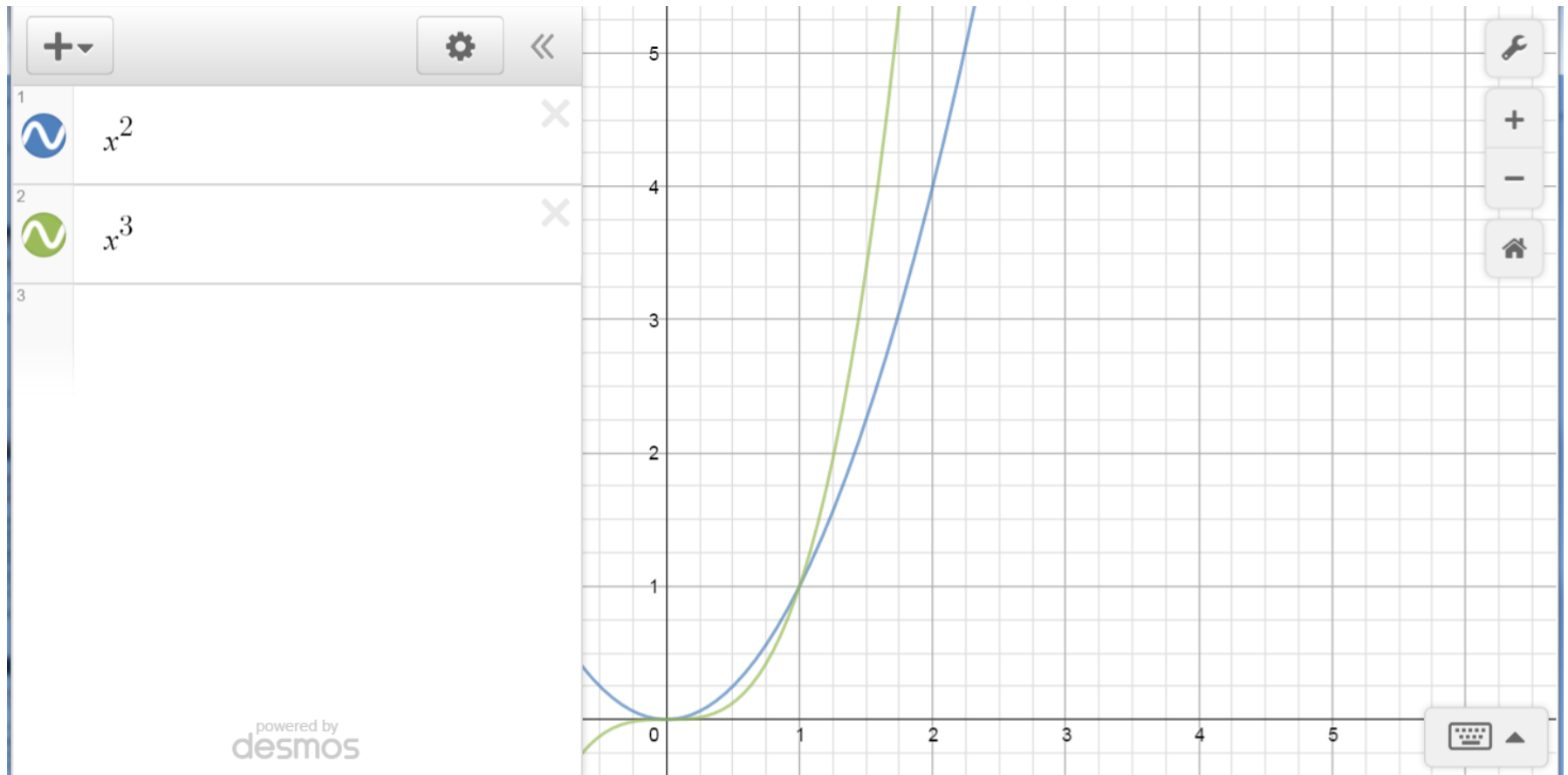
□ From there: $1 / n \leq K$, and since $n \geq 1$ then $K \geq 1$

□ Hence, for $K \geq 1$ and $n \geq 1$, $f(n) = O(g(n))$

Big-O Notation Formally Defined /6

■ Example2 Visualized:

- For $f(x) = x^2$ and $g(x) = x^3$, it follows that $f(x) = O(g(x))$ for $x \geq 1$



Big-O Notation Formally Defined /7

- Another approach to comparing function growth:

- Compute $\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)}$
- If the value is 0, then $f(n)$ grows slower than $g(n)$; that is, $f(n) = O(g(n))$ (e.g., n / n^2)
- If the value is a constant c , then $f(n)$ grows as fast as $g(n)$; that is, $f(n) = O(g(n))$ (e.g., $2n / n$)
- If the value is infinity ∞ , then $f(n)$ grows faster than $g(n)$; that is, $g(n) = O(f(n))$ (e.g., n^2 / n)

Big-O Notation Formally Defined /8

■ Example using limits:

- Let $f(n) = n^2$ and $g(n) = 2^n$. Show that $f(n) = O(g(n))$

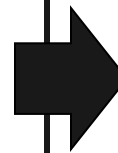
- Steps:
$$\begin{aligned}\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} &= \lim_{n \rightarrow \infty} \frac{n^2}{2^n} \\ &= \lim_{n \rightarrow \infty} \frac{2n}{\ln(2) 2^n} \text{ (using L'Hospital's Rule)} \\ &= \lim_{n \rightarrow \infty} \frac{2}{\ln(2)^2 2^n} \text{ (using L'Hospital's Rule)} \\ &= \frac{2}{\ln(2)^2} \lim_{n \rightarrow \infty} \frac{1}{2^n} = 0\end{aligned}$$

- Hence, $f(n) = O(g(n))$

From Source Code to Big-O Notation /1

- How can we compute the Big-O measurement directly from source code?
 - Express each loop as a summation/sigma, Σ
 - For segments of code that are repeated on each iteration, express each segment as a constant (e.g., a)
 - For nested loops, use nested summations (e.g., $\Sigma \Sigma$)
 - Finally, use summation formulas for simplification

```
for i = 0 to n - 2 do {  
    for j = i + 1 to n - 1 do {  
        for k = i to n do {  
            // constant steps  
        }  
    }  
}
```



$$f(n) = \sum_{i=0}^{n-2} \sum_{j=i+1}^{n-1} \sum_{k=i}^n a$$

From Source Code to Big-O Notation /2

$$f(n) = \sum_{i=0}^{n-2} \sum_{j=i+1}^{n-1} \sum_{k=i}^n a =$$

$$a \sum_{i=0}^{n-2} \sum_{j=i+1}^{n-1} (n - i + 1) = a \sum_{i=0}^{n-2} (n - i - 1)(n - i + 1) =$$

$$a((n + 1)(n - 1) + n(n - 2) + \cdots + 3 * 1) =$$

$$a \sum_{j=1}^{n-1} (j + 2)j = a \sum_{j=1}^{n-1} j^2 + a \sum_{j=1}^{n-1} 2j =$$

$$a \frac{(n - 1)n(2n - 1)}{6} + 2a \frac{(n - 1)n}{2} =$$

$$a \frac{n(n - 1)(2n + 5)}{6} = a \left(\frac{1}{3}n^3 + \frac{1}{2}n^2 - \frac{5}{6}n \right) = O(n^3)$$

Analysis of Recursive Algorithms /1

- **How can we compute the Big-O measurement for recursive algorithms?**
 - Define the base cases and the recursive case
 - Use backwards substitution to go from the recursive case down to the base cases
 - Use summation and other formulas for simplification

```
int BinarySearch(int A[], int L, int R, int K) {  
    // A must be already sorted for this to work  
    int mid = (L + R) / 2;  
    if (R < L)  
        return -1;  
    else if (A[mid] == K)  
        return mid;  
    else if (K > A[mid])  
        return BinarySearch(A, mid + 1, R, K);  
    else  
        return BinarySearch(A, L, mid - 1, K);  
}
```



Let $n = R - L + 1$, then
 $T(1) = a$
 $T(n) = b + T(n/2)$

Analysis of Recursive Algorithms /2

Let $n = R - L + 1$, then
 $T(1) = a$
 $T(n) = b + T(n/2)$

$$\begin{aligned}T(n) &= b + T\left(\frac{n}{2}\right) \\&= b + b + T\left(\frac{n}{4}\right) \\&= b + b + b + T\left(\frac{n}{8}\right) \\&= \dots \\&= ib + T\left(\frac{n}{2^i}\right)\end{aligned}$$

**Backwards
substitution**

When $(n / 2^i) = 1$, let $i = c$

It follows that $(n / 2^c) = 1$, and
 $n = 2^c$, so $c = \log_2(n)$

$$\begin{aligned}T(n) &= cb + T\left(\frac{n}{2^c}\right) \\&= cb + T(1) \\&= b\log_2(n) + a \\&= O(\log(n))\end{aligned}$$

Lecture Notes Summary

- **What do you need to know?**
 - Measuring algorithm performance
 - Using Big-O to classify algorithms
 - Defining Big-O notation formally
 - Mapping source code to Big-O
 - Analyzing recursive algorithms

Food for Thought

- **Read:**

- Chapter 5 (Algorithmic Analysis) from the course handbook

- **Additional Readings:**

- Section 1.2 (Running Time Analysis) and Appendix B (More Big-O Notation) from “Data Structures and Other Objects Using C++” by Main and Savitch