



# Algorithm Efficiency

- ◆ **There are often many approaches (algorithms) to solve a problem. How do we choose between them?**
- ◆ **At the heart of computer program design are two (sometimes conflicting) goals:**
  - To design an algorithm that is easy to understand, code and debug.
  - To design an algorithm that makes efficient use of the computer's resources.



# Algorithm Efficiency

- ◆ **Goal (1) is the concern of Software Engineering.**
- ◆ **Goal (2) is the concern of data structures and algorithm analysis.**
- ◆ **When goal (2) is important, how do we measure an algorithm's cost?**



# How to Measure Efficiency?

- ◆ **Empirical comparison (run programs).**
- ◆ **Asymptotic Algorithm Analysis.**
- ◆ **Critical resources:**
- ◆ **Factors affecting running time:**



# How to Measure Efficiency?

- ◆ For most algorithms, running time depends on "size" of the input.
- ◆ Running time is expressed as  $T(n)$  for some function  $T$  on input size  $n$ .



# Examples of Growth Rate

## ◆ Example 1:

```
int largest(int* array, int n)    // Find largest value
{ int currlarge = array[0];      // Store largest seen
  for (int i=1; i<n; i++)        // For each element
    if (array[i] > currlarge)    // If largest
      currlarge = array[i];      // Remember it
  return currlarge;              // Return largest
}
```

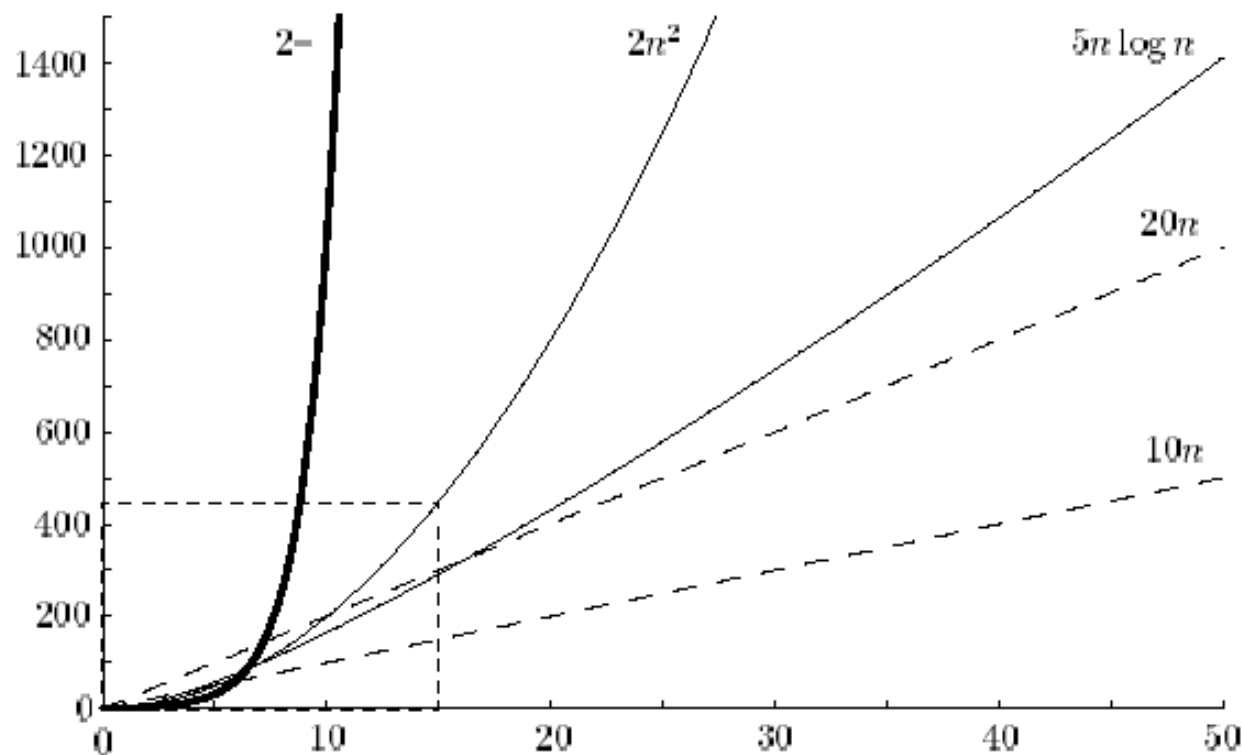


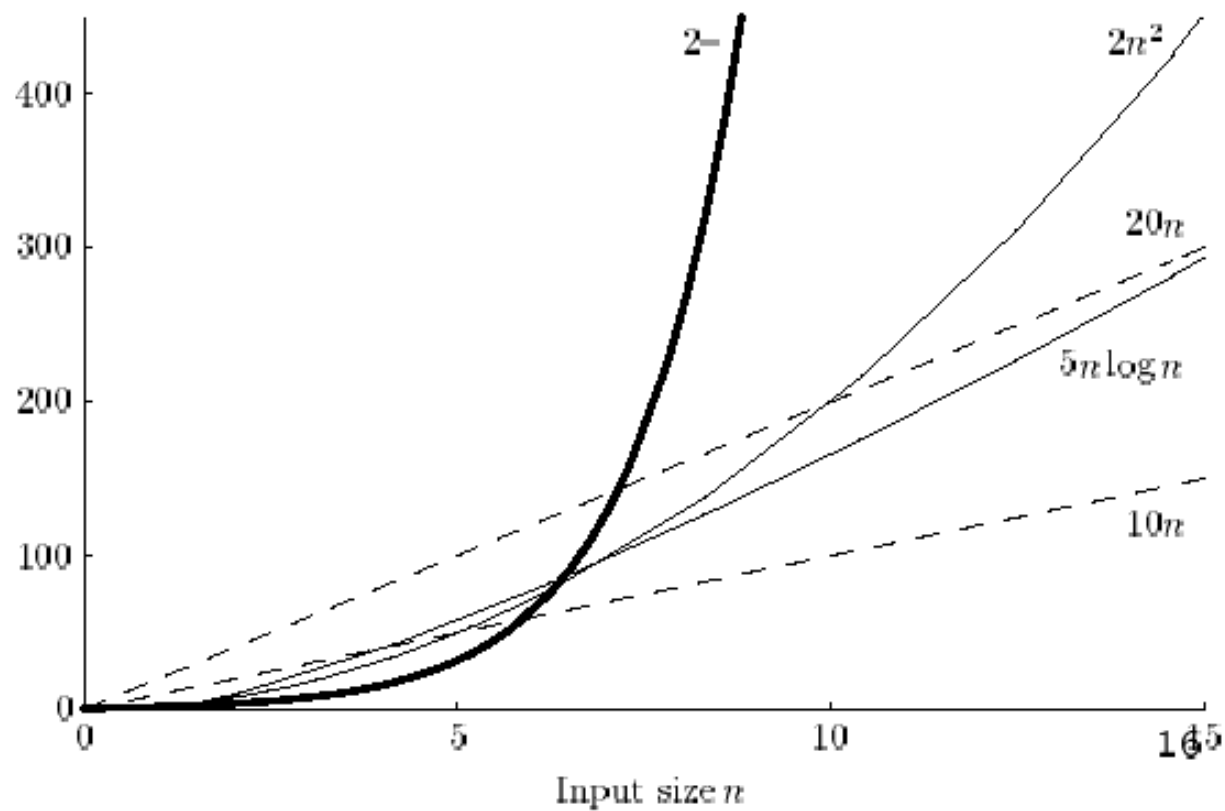
# Examples of Growth Rate

◆ **Example 2:**  
**sum = 0;**  
**for (i=1; i<=n; i++)**  
    **for (j=1; j<=n; j++)**  
        **sum++;**



## Growth Rate Graph









# Best, Worst and Average Cases

- ◆ **Not all inputs of a given size take the same time.**
- ◆ **Sequential search for  $K$  in an array of  $n$  integers:**
  - Begin at first element in array and look at each element in turn until  $K$  is found.



# Best, Worst and Average Cases

- ◆ **Best Case:**
- ◆ **Worst Case:**
- ◆ **Average Case:**
- ◆ **While average time seems to be the fairest measure, it may be difficult to determine.**
- ◆ **When is worst case time important?**



# Faster Computer or Algorithm?

- ◆ What happens when we buy a computer 10 times faster?



$T(n)$	$n$	$n'$	Change	$n'/n$
$10n$	1,000	10,000	$n' = 10n$	10
$20n$	500	5,000	$n' = 10n$	10
$5n \log n$	250	1,842	$\sqrt{10}n < n' < 10n$	7.37
$2n^2$	70	223	$n' = \sqrt{10}n$	3.16
$2^n$	13	16	$n' = n + 3$	--

$n$ : Size of input that can be processed in one hour (10,000 steps).

$n'$ : Size of input that can be processed in one hour on the new machine (100,000 steps).

# Asymptotic Analysis: Big-oh

- ◆ **definition:** (Big-Oh)  $T(N)$  is  $O(F(N))$  if there are positive constants  $c$  and  $N_0$  such that  $T(N) \leq cF(N)$  when  $N \geq N_0$ .
- ◆ **definition:** (Big-Omega)  $T(N)$  is  $\Omega(F(N))$  if there are positive constants  $c$  and  $N_0$  such that  $T(N) \geq cF(N)$  when  $N \geq N_0$ .
- ◆ **definition:** (Big-Theta)  $T(N)$  is  $\Theta(F(N))$  if and only if  $T(N)$  is  $O(F(N))$  and  $T(N)$  is  $\Omega(F(N))$ .
- ◆ **definition:** (Little-Oh)  $T(N)$  is  $o(F(N))$  if and only if  $T(N)$  is  $O(F(N))$  and  $T(N)$  is not  $\Omega(F(N))$ .

# Meanings

## ◆ Meanings of the various growth functions

### Mathematical Expression

### Relative Rates of Growth

$$T(N) = O(F(N))$$

Growth of  $T(N)$  is  $\leq$  growth of  $F(N)$ .

$$T(N) = \Omega(F(N))$$

Growth of  $T(N)$  is  $\geq$  growth of  $F(N)$ .

$$T(N) = \Theta(F(N))$$

Growth of  $T(N)$  is  $=$  growth of  $F(N)$ .

$$T(N) = o(F(N))$$

Growth of  $T(N)$  is  $<$  growth of  $F(N)$ .



# Asymptotic Analysis: Big-oh

- ◆ **Usage:** The algorithm is in  $O(n^2)$  in [best, average, worst] case.
- ◆ **Meaning:** For all data sets big enough (i.e.,  $n > n_0$ ), the algorithm always executes in less than  $cf(n)$  steps [in best, average or worst case].



# Asymptotic Analysis: Big-oh

- ◆ **Upper Bound.**
- ◆ **Example: if  $T(n) = 3n^2$  then  $T(n)$  is in  $O(n^2)$ .**
- ◆ **Wish tightest upper bound:**
- ◆ **While  $T(n) = 3n^2$  is in  $O(n^3)$ , we prefer  $O(n^2)$ .**



# Simplifying Rules:

- ◆ If  $f(n)$  is in  $O(g(n))$  and  $g(n)$  is in  $O(h(n))$ , then  $f(n)$  is in  $O(h(n))$ .
- ◆ If  $f(n)$  is in  $O(kg(n))$  for any constant  $k > 0$ , then  $f(n)$  is in  $O(g(n))$ .
- ◆ If  $f_1(n)$  is in  $O(g_1(n))$  and  $f_2(n)$  is in  $O(g_2(n))$ , then  $(f_1 + f_2)(n)$  is in  $O(\max(g_1(n), g_2(n)))$ .

# Simplifying Rules:

- ◆ If  $f_1(n)$  is in  $O(g_1(n))$  and  $f_2(n)$  is in  $O(g_2(n))$  then  $f_1(n)f_2(n)$  is in  $O(g_1(n)g_2(n))$ .



# Running Time of a Program

- ◆ **Example 1:**

**`a = b;`**

**This assignment takes constant time, so it is(1).**

- ◆ **Example 2:**

**`sum = 0;`**

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

**`sum += n;`**



# Running Time of a Program

- ◆ **Example 3:**

**sum = 0;**

**for (j=1; j<=n; j++) // First for loop**

**for (i=1; i<=j; i++) // is a double loop**

**sum++;**

**for (k=0; k<n; k++) // Second for loop**

**A[k] = k;**

# More Examples

- ◆ **Example 4.**

```
sum1 = 0;
```

```
for (i=1; i<=n; i++) // First double loop
```

```
    for (j=1; j<=n; j++) // do n times
```

```
        sum1++;
```

```
sum2 = 0;
```

```
for (i=1; i<=n; i++) // Second double loop
```

```
    for (j=1; j<=i; j++) // do i times
```

```
        sum2++;
```

# Other Control Statements

- ◆ **while loop: analyze like a for loop.**
- ◆ **if statement: Take greater complexity of then/else clauses.**
- ◆ **switch statement: Take complexity of most expensive case.**
- ◆ **Subroutine call: Complexity of the subroutine.**



# Analyzing Problems

- ◆ **Upper bound: Upper bound of best known algorithm.**
- ◆ **Lower bound: Lower bound for every possible algorithm.**



# Space Bounds

- ◆ **Space bounds can also be analyzed with asymptotic complexity analysis.**
- ◆ **Time: Algorithm**
- ◆ **Space: Data Structure**





# the maximum contiguous subsequence sum problem

- ◆ if the input is  $\{-2, \mathbf{11}, \mathbf{-4}, \mathbf{13}, -5, 2\}$ , then the answer is 20, which represents the contiguous subsequence encompassing items 2 through 4 (shown in boldface type).
- ◆ As a second example, for the input  $\{1, -3, \mathbf{4}, \mathbf{-2}, \mathbf{-1}, \mathbf{6}\}$ , the answer is 7 for the subsequence encompassing the last four items.
- ◆ The problem statement gives a maximum contiguous subsequence sum of 0 for the case in which all input integers are negative.

- ◆ the obvious  $O(N^3)$  algorithm
- ◆ an improved  $O(N^2)$  algorithm
- ◆ a linear algorithm