

## Introduction to Algorithms

DongYeon Kim
Department of Multimedia Engineering
Dongguk University



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### Introduction

- Order of growth
  - > The order of growth of the running time of an algorithm
    - ✓ Gives a simple characterization of the algorithm's efficiency
    - ✓ For large enough inputs, the multiplicative constants and lower-order terms are
      dominated by the effects of the input size itself

Ex) 
$$an^2 + bn + c \rightarrow \Theta(n^2)$$

✓ Enables to compare the relative performance of alternative algorithms Ex) Merge sort :  $\theta(n \log n)$  < Insertion sort :  $\theta(n^2)$ 

#### Asymptotic efficiency of algorithm

- ✓ How the running time of an algorithm increases with the size of the input in the limit.
- ✓ Several standard methods for simplifying the asymptotic analysis of algorithms

### Asymptotic notation

- Asymptotic notation, functions, and running times
  - ➤ Asymptotic notation
    - ✓ Describe the running times of algorithms
    - ✓ Applies to functions Ex) What we were writing as  $\Theta(n^2)$  was the function about  $an^2 + bn + c$

#### > Functions

- ✓ The functions to which we apply asymptotic notation will usually characterize the running times of algorithms
- ✓ Characterize other aspect of algorithms amount of space they use

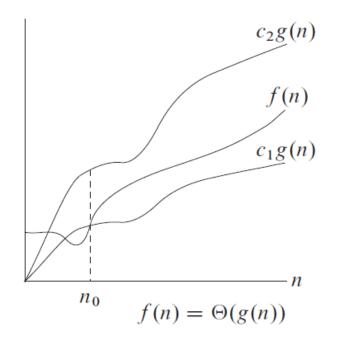
#### > Running time

- ✓ Commonly interested in the worst case
- ✓ Characterize the running time no matter what the input

### Asymptotic notation

- **②** notation (Big−**②** notation)
  - Definition

$$\Theta(g(n)) = \{f(n) : \text{ there exist positive constants } c_1, c_2, \text{ and } n_0 \text{ such that } 0 \le c_1 g(n) \le f(n) \le c_2 g(n) \text{ for all } n \ge n_0 \}$$
.



- $\checkmark \ \Theta(g(n))$  is the set of functions
- $\checkmark$  Function f(n) is running time of algorithm
- $\checkmark$   $n_0$  is the minimum possible value
- $\checkmark$  f(n) = Θ(g(n)) means f(n) belongs to the set Θ(g(n)) ( f(n) ∈ Θ(g(n)) )
- For all values of n to the right of  $n_0$ , the value of f(n) lies at or above  $c_1g(n)$  and at or below  $c_2g(n)$
- $\checkmark g(n)$  is asymptotically tight bound for f(n)

### Asymptotic notation

#### • • notation

- ightharpoonup Example: Prove  $\frac{1}{2}n^2 3n = \Theta(n^2)$ 
  - $\checkmark$  Let  $f(n) = \frac{1}{2}n^2 3n$ ,  $g(n) = \theta(n^2)$
  - ✓ According to definition

$$c_1 n^2 \le \frac{1}{2} n^2 - 3n \le c_2 n^2$$

✓ For all  $n \ge n_0$ , dividing by  $n^2$ 

$$c_1 \le \frac{1}{2} - \frac{3}{n} \le c_2$$

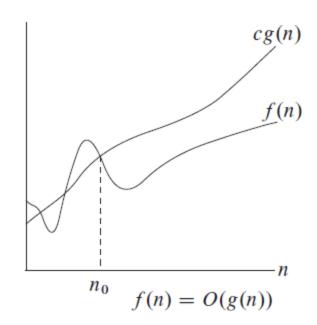
- $\checkmark$  First, if  $c_1 \le \frac{1}{14} \& n \ge 7 \rightarrow c_1 \le \frac{1}{2} \frac{3}{n}$  is always true
- $\checkmark$  Second, if  $c_2 \ge \frac{1}{2} \& n \ge 1 \rightarrow c_2 \ge \frac{1}{2} \frac{3}{n}$  is always true
- $\checkmark$  So there exist  $c_1$ ,  $c_2$ ,  $n_0$  so we can verify that  $\frac{1}{2}n^2 3n = \theta(n^2)$
- The important thing is that there exist some set about  $c_1$ ,  $c_2$ ,  $n_0$ , not which number of  $c_1$ ,  $c_2$ ,  $n_0$  choosen

  BigDataLab dong

### Asymptotic notation

- O notation (Big-O notation)
  - Definition

$$O(g(n)) = \{f(n) : \text{ there exist positive constants } c \text{ and } n_0 \text{ such that } 0 \le f(n) \le cg(n) \text{ for all } n \ge n_0 \}$$
.

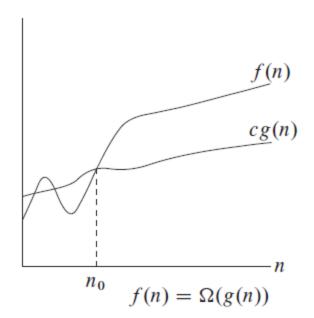


- ✓ Only have an asymptotic upper bound
- ✓ f(n) = O(g(n)) means f(n) belongs to the set O(g(n))( $f(n) \in O(g(n))$ )
- ✓  $f(n) = \Theta(g(n))$  implies f(n) = O(g(n))( $\Theta(g(n)) \subseteq O(g(n))$ )
- ✓ For all values of n to the right of  $n_0$ , the value of f(n) lies at or below cg(n)
- $\checkmark g(n)$  is an asymptotic upper bound on f(n)

### Asymptotic notation

- $\Omega$  notation (Big- $\Omega$  notation)
  - Definition

$$\Omega(g(n)) = \{f(n) : \text{ there exist positive constants } c \text{ and } n_0 \text{ such that } 0 \le cg(n) \le f(n) \text{ for all } n \ge n_0 \}$$
.



- ✓ Only have an asymptotic lower bound
- $\checkmark$  f(n) = Ω(g(n)) means f(n) belongs to the set Ω(g(n)) ( f(n) ∈ Ω(g(n)) )
- ✓ For all values of n to the right of  $n_0$ , the value of f(n) lies at or above cg(n) and

#### Theorem 3.1

For any two functions f(n) and g(n), we have  $f(n) = \Theta(g(n))$  if and only if f(n) = O(g(n)) and  $f(n) = \Omega(g(n))$ .



### Asymptotic notation

- o notation (Little-o notation)
  - Definition

```
o(g(n)) = \{f(n) : \text{ for any positive constant } c > 0, \text{ there exists a constant } n_0 > 0 \text{ such that } 0 \le f(n) < cg(n) \text{ for all } n \ge n_0 \}.
```

- ✓ Denote an upper bound that is not asymptotically tight (Relaxed upper bound)
- ✓ Big-O notation, the bound  $0 \le f(n) \le cg(n)$  holds for some constant c > 0
- ✓ Little-o notation, the bound  $0 \le f(n) < cg(n)$  holds for all constants c > 0
- $\checkmark$  Ex)  $2n = o(n^2)$ , but  $2n^2 \neq o(n^2)$
- $\checkmark$  o-notation, function f(n) becomes insignificant relative to g(n) as n approaches infinity

$$\lim_{n \to \infty} \frac{f(n)}{g(n)} = 0$$

### Asymptotic notation

- $\omega$  notation (Little- $\omega$  notation)
  - Definition

$$\omega(g(n)) = \{f(n) : \text{ for any positive constant } c > 0, \text{ there exists a constant } n_0 > 0 \text{ such that } 0 \le cg(n) < f(n) \text{ for all } n \ge n_0 \}$$
.

- ✓ Denote a lower bound that is not asymptotically tight (Relaxed lower bound)
- ✓ Big- $\Omega$  notation, the bound  $0 \le cg(n) \le f(n)$  holds for some constant c > 0
- ✓ Little- $\omega$  notation, the bound  $0 \le cg(n) < f(n)$  holds for all constants c > 0
- $\checkmark$  Ex)  $\frac{n^2}{2} = \omega(n)$ , but  $\frac{n^2}{2} \neq \omega(n^2)$
- ✓ o-notation, function f(n) becomes insignificant relative to g(n) as n approaches infinity

$$\lim_{n \to \infty} \frac{f(n)}{g(n)} = \infty$$

#### Introduction

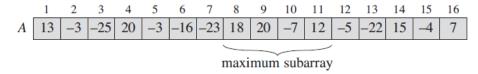
- Divide and Conquer
  - > Solve a problem recursively, applying three steps
    - ✓ Divide the problem into some subproblems that are smaller instances of the same problem
    - ✓ Conquer the subproblems by solving them recursively.
      - i. If the subproblem sizes are small enough, just solve the subproblems in a straightforward manner
      - ii. Recursive case: subproblems are large enough to solve recursively
      - iii. Base case: subproblems become small enough that no longer recurse
    - ✓ Combine the solutions to the subproblems into the original problem
  - > Sometimes, we solve subproblems that are not the same as the original problem
    - ✓ consider solving such subproblems as combine step
  - ➤ We will solve two Divide and Conquer problem
    - ✓ maximum-subarray problem
    - ✓ Multiplying N x N matrices



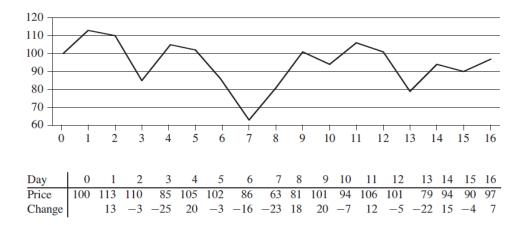
### The maximum subarray problem

#### Definition

- Task to find the series of continuous elements with the maximum sum in any given array
- ➤ It is trivial if all elements in the array are non-negative



#### Price of stock problem



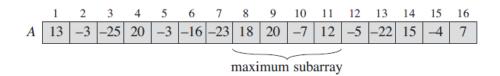
- ✓ X axis: date Y axis: stock price
- ✓ The bottom row of the table gives the change in price from the previous day
- ✓ Have to find maximum profit → find maximum subarray in bottom row of the table



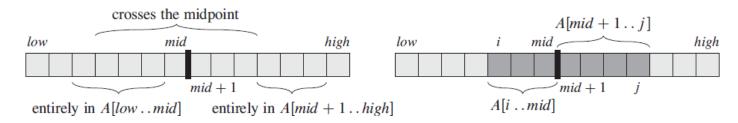
### The maximum subarray problem

- Brute Force solution
  - > Just try every possible pair of buy and sell dates.

$$\triangleright \binom{n}{2} = \Theta(n^2)$$



Divide and Conquer solution

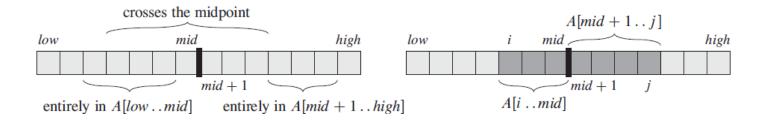


- $\triangleright$  We want to find maximum subarray of the subarray A[low..high]
- $\triangleright$  Maximum subarray : A[i..j]
- > We will find maximum subarray in three cases



### The maximum subarray problem

Divide and Conquer Solution



#### ➤ We will find maximum subarray in three cases

- entirely in the subarray A[low..mid], so that  $low \le i \le j \le mid$ ,
- entirely in the subarray A[mid + 1..high], so that  $mid < i \le j \le high$ , or
- crossing the midpoint, so that  $low \le i \le mid < j \le high$ .
  - $\checkmark$  Any contiguous subarray A[i..j] of A[low..high] must lie in exactly one of the following places
  - ✓ We can find maximum subarrays of A[low..mid] and A[mid + 1..high] recursively
    - i. Two subproblems are smaller instances of the Original problem
  - ✓ all that left to do is find a maximum subarray that crosses the midpoint.



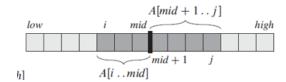


### The maximum subarray problem

- Divide and Conquer Solution
  - > Find a maximum subarray that crosses the midpoint

```
FIND-MAX-CROSSING-SUBARRAY (A, low, mid, high)
    left-sum = -\infty
 2 \quad sum = 0
    for i = mid downto low
        sum = sum + A[i]
        if sum > left-sum
            left-sum = sum
            max-left = i
    right-sum = -\infty
    sum = 0
    for j = mid + 1 to high
        sum = sum + A[j]
        if sum > right-sum
            right-sum = sum
            max-right = j
    return (max-left, max-right, left-sum + right-sum)
```

- ✓ This problem is not a smaller instance of original problem
   → it has the added restriction that the subarray must cross the midpoint
- ✓ Find maximum subarrays of the form A[i..mid] and A[mid + 1..j]



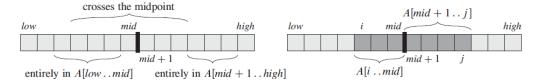
- ✓ Line 1 ~ 7 : get max-left
- ✓ Line 8 ~ 14 get max-right
- ✓ The total number of iteration : high low + 1 = n
- ✓ It takes  $\theta(n)$



### The maximum subarray problem

- Divide and Conquer Solution
  - > FIND-MAXIMUM-SUBARRAY(A, low, high)

```
FIND-MAXIMUM-SUBARRAY (A, low, high)
    if high == low
         return (low, high, A[low])
                                              // base case: only one element
    else mid = \lfloor (low + high)/2 \rfloor
         (left-low, left-high, left-sum) =
             FIND-MAXIMUM-SUBARRAY (A, low, mid)
 5
         (right-low, right-high, right-sum) =
             FIND-MAXIMUM-SUBARRAY (A, mid + 1, high)
         (cross-low, cross-high, cross-sum) =
 6
             FIND-MAX-CROSSING-SUBARRAY (A, low, mid, high)
         if left-sum \geq right-sum and left-sum \geq cross-sum
             return (left-low, left-high, left-sum)
         elseif right-sum \ge left-sum and right-sum \ge cross-sum
             return (right-low, right-high, right-sum)
10
11
         else return (cross-low, cross-high, cross-sum)
```



- ✓ Line 4~5: recursively solve the problem (left & right)
- ✓ Line 6: find max crossing subarray
- ✓ Line 7~11: fine maximum subarray out of the three cases



### The maximum subarray problem

- Analyzing Divide and Conquer algorithm
  - ➤ Set up a recurrence of the recursive FIND-MAXIMUM-SUBARRAY procedure
    - $\checkmark T(n)$ : the running time of FIND-MAXIMUM-SUBARRAY on a subarray of n elements
    - ✓ When  $n = 1, T(1) = \theta(1)$
    - ✓ When n > 1
      - i. Recursively solve left & right subarray spend T(n/2) time solving each of them
      - ii. As we already seen, FIND-MAX-CROSSING-SUBARRAY takes  $\theta(n)$  time
      - iii. The left line take only  $\theta(1)$  time
    - ✓ Therefore, we have

$$T(n) = \Theta(1) + 2T(n/2) + \Theta(n) + \Theta(1)$$

$$= 2T(n/2) + \Theta(n).$$

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1, \\ 2T(n/2) + \Theta(n) & \text{if } n > 1. \end{cases}$$

✓ According to Master method  $T(n) = \theta(n \log n)$  → asymptotically faster than the brute-force



## Strassen's algorithm for matrix multiplication

#### Matrix multiplication

#### **>** Definition

```
✓ Input: A = (a_{ij}) and B = (b_{ij}) are square n \times n matrices
```

✓ Output: 
$$C = A \times B$$

$$c_{ij} = \sum_{k=1}^{n} a_{ik} \cdot b_{kj}$$
 for  $i, j = 1, 2, ..., n$ , by

#### ▶ pseudocode

SQUARE-MATRIX-MULTIPLY (A, B)

```
\begin{array}{ll}
1 & n = A.rows \\
2 & \text{let } C \text{ be a new } n \times n \text{ matrix} \\
3 & \textbf{for } i = 1 \textbf{ to } n \\
4 & \textbf{for } j = 1 \textbf{ to } n \\
5 & c_{ij} = 0 \\
6 & \textbf{for } k = 1 \textbf{ to } n \\
7 & c_{ij} = c_{ij} + a_{ik} \cdot b_{kj} \\
8 & \textbf{return } C
\end{array}
```

✓ The running time for matrix multiplication

$$T(n) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} c = cn^{3} = \theta(n^{3})$$

✓ We will study about simple divide–and–conquer algorithm and Strassen's algorithm which runs in  $O(n^{2.81})$  time

## Strassen's algorithm for matrix multiplication

- A simple divide-and-conquer algorithm
  - ➤ Divide
    - ✓ Divide  $n \times n$  matrices into four  $n/2 \times n/2$  matrices
    - ✓ Suppose that we partition each of A, B and C into four  $n/2 \times n/2$  matrices

$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}, \quad B = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix}, \quad C = \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix},$$

✓ We can rewrite the equation  $C = A \times B$  as

$$\begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \cdot \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix}.$$

#### ➤ Conquer & Combine

✓ Perform 8 multiplication and 4 addition of  $n/2 \times n/2$  submatrices recursively

$$C_{11} = A_{11} \cdot B_{11} + A_{12} \cdot B_{21} , C_{21} = A_{21} \cdot B_{11} + A_{22} \cdot B_{21} ,$$
  
 $C_{12} = A_{11} \cdot B_{12} + A_{12} \cdot B_{22} , C_{22} = A_{21} \cdot B_{12} + A_{22} \cdot B_{22} .$ 

## Strassen's algorithm for matrix multiplication

- A simple divide-and-conquer algorithm
  - ➤ Pseudocode & analyzing

```
SQUARE-MATRIX-MULTIPLY-RECURSIVE (A, B)
 1 n = A.rows
    let C be a new n \times n matrix
    if n == 1
        c_{11} = a_{11} \cdot b_{11}
    else partition A, B, and C as in equations (4.9)
        C_{11} = \text{SQUARE-MATRIX-MULTIPLY-RECURSIVE}(A_{11}, B_{11})
              + SQUARE-MATRIX-MULTIPLY-RECURSIVE (A_{12}, B_{21})
        C_{12} = \text{SQUARE-MATRIX-MULTIPLY-RECURSIVE}(A_{11}, B_{12})
             + SQUARE-MATRIX-MULTIPLY-RECURSIVE (A_{12}, B_{22})
        C_{21} = \text{SQUARE-MATRIX-MULTIPLY-RECURSIVE}(A_{21}, B_{11})
 8
             + SQUARE-MATRIX-MULTIPLY-RECURSIVE (A_{22}, B_{21})
        C_{22} = \text{SQUARE-MATRIX-MULTIPLY-RECURSIVE}(A_{21}, B_{12})
              + SQUARE-MATRIX-MULTIPLY-RECURSIVE (A_{22}, B_{22})
10 return C
```

- ✓ Line5: do not create 12 new  $n/2 \times n/2$  matrices
  - $\rightarrow$  would spend  $\theta(n^2)$  time to copy entries
  - → use index calculation
- ✓ Index Calculation: identify submatrix by a range of row & column indices of the original matrix  $\rightarrow$  spend  $\theta(1)$  time
- $\checkmark$  When n = 1,  $T(1) = \theta(1)$
- ✓ When n > 1,
  - $\rightarrow$  call recursive function 8 times takes  $8T\left(\frac{n}{2}\right)$
  - $\rightarrow$  four matrix additions takes  $\theta(n^2)$  times



- Strassen's algorithm for matrix multiplication
  - A simple divide-and-conquer algorithm
    - ➤ Pseudocode & analyzing

$$T(n) = \underbrace{\Theta(1) + 8T(n/2) + \Theta(n^2)}_{8T(n/2) + \Theta(n^2)} + \underbrace{\Theta(n^2)}_{8T(n/2) + \Theta(n^2)} \text{ if } n = 1,$$
Index Calculation 8 Multiplications 4 Additions

- $\checkmark$  According to master method  $T(n) = \theta(n^3)$
- ✓ This simple divide- and-conquer approach is no faster than the straightforward SQUARE-MATRIX-MULTIPLY procedure
- ✓ So now introduce Strassen's method

## Strassen's algorithm for matrix multiplication

- Strassen's method
  - > Differences from the previous method
    - ✓ The key to Strassen's method is to make the recursion tree less complicated
    - ✓ It performs only seven recursive multiplications (not eight)
  - ➤ How does it work?
    - ✓ Divide the input matrices A, B and C into  $n/2 \times n/2$  submatrices
      - i. takes  $\theta(1)$  time by index calculation
    - ✓ Create 10 matrices  $s_1, s_2, ..., s_{10}$ , each of which is  $n/2 \times n/2$  submatrices
      - Matrices are the sum or difference of two matrices created in step 1
      - ii. Takes  $\theta(n^2)$  times

$$S_1 = B_{12} - B_{22}$$
,  $S_6 = B_{11} + B_{22}$ ,  
 $S_2 = A_{11} + A_{12}$ ,  $S_7 = A_{12} - A_{22}$ ,  
 $S_3 = A_{21} + A_{22}$ ,  $S_8 = B_{21} + B_{22}$ ,  
 $S_4 = B_{21} - B_{11}$ ,  $S_9 = A_{11} - A_{21}$ ,  
 $S_5 = A_{11} + A_{22}$ ,  $S_{10} = B_{11} + B_{12}$ .



## Strassen's algorithm for matrix multiplication

- Strassen's method
  - > How does it work?
    - ✓ Using the submatrices created in step 1 and the 10 matrices created in step 2, recursively compute seven matrix products  $P_1$ ,  $P_2$ , ...,  $P_7$  which are  $n/2 \times n/2$  submatrices
      - i. Require us to perform seven multiplications of  $n/2 \times n/2$  matrices
      - ii. Takes 7T(n/2) times

- ✓ Compute the desired submatrices  $C_{11}$ ,  $C_{12}$ ,  $C_{21}$ ,  $C_{22}$  of the result matrix C by adding and subtracting carious combinations of the  $P_i$  matrices.
  - i. Takes  $\theta(n^2)$  times

$$C_{11} = P_5 + P_4 - P_2 + P_6$$
  $C_{21} = P_3 + P_4$   $C_{12} = P_1 + P_2$   $C_{22} = P_5 + P_1 - P_3 - P_7$ 



- Strassen's algorithm for matrix multiplication
  - Strassen's method
    - ➤ Analyzing algorithm

$$T(n) = \theta(1) + \theta(n^2) + 7T\left(\frac{n}{2}\right) + \theta(n^2)$$

$$= 7T\left(\frac{n}{2}\right) + \theta(n^2)$$

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1, \\ 7T(n/2) + \Theta(n^2) & \text{if } n > 1. \end{cases}$$
Index Calculation

Create 10  $s_i$  Calculate 7  $P_i$  Compute  $c_i$ 

- $\checkmark$  According to master method  $T(n) = \theta(n^{\log 7}) = \theta(n^{2.8})$
- ✓ Strassen's algorithm, comparing with previous methods, is asymptotically faster!!

# Thank You!

