# ALGORITHMS AND LAB (CSE130) Dynamic Programming

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Note: These notes are prepared from the following resources.

- (main text)Foundations of Algorithms, by Richard Neapolitan and Kumarss Naimipour
- O Python Algorithm (파이썬 알고리즘) by Y.K. Choi (2021) (Korean)
- Introduction to the Design and Analysis of Algorithms by Anany Levitin
- Introduction to Algorithms, by By Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest and Clifford Stein
- https://www.geeksforgeeks.org

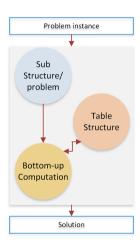
### CONTENTS

- Computing Binomial Coefficients
- PATH COUNTING PROBLEM
- Coin-collecting Problem
- CHAINED MATRIX MULTIPLICATION
- **OPTIMAL BINARY SEARCH TREE**

### DYNAMIC PROGRAMMING APPROACH

### Dynamic Programming Approach

- Dynamic programming is a bottom-up approach for solving problems with overlapping subproblems.
- There are basically three elements that characterize a dynamic programming algorithm:
  - Substructure: Decompose the given problem into smaller subproblems. Express the solution of the original problem in terms of the solution for smaller problems. (Establish a recursive property)
  - Table Structure: After solving the sub-problems, store the results to the sub problems in a table.
  - Bottom-up Computation: Using table, combine the solution of smaller subproblems to solve larger subproblems and eventually arrives at a solution to complete problem.



 The word "programming" in the name of this technique stands for "planning" and does not refer to computer programming.

#### **Example: Computing Binomial Coefficients**

- Binomial Theorem  $(a+b)^n = \sum_{k=0}^n \frac{n!}{k!(n-k)} a^k b^{n-k}$
- Binomial coefficients:  $\binom{n}{k} = \frac{n!}{k!(n-k)}$
- Another Representation:

$$\left( \begin{array}{c} n \\ k \end{array} \right) = \left\{ \begin{array}{c} \left( \begin{array}{c} n-1 \\ k-1 \end{array} \right) + \left( \begin{array}{c} n-1 \\ k \end{array} \right), \ 0 < k < n \\ 1 \end{array} \right.$$

Establish a recursive property.

$$B\left[i\right]\left[j\right] = \left\{ \begin{array}{c} B\left[i-1\right]\left[j-1\right] + B\left[i-1\right]\left[j\right], & 0 < j < i \\ 1, & j = 0 \text{ or } j = i \end{array} \right.$$

$$\begin{pmatrix} n \\ k \end{pmatrix} = \frac{n!}{k! * (n-k)!}$$

$$= \frac{(n-1)! * n}{k! * (n-k)!}$$

$$= \frac{(n-1)! * n}{((k-1)! * k * (n-k-2)! * (n-k-1) * (n-k))}$$

$$= \frac{(n-1)!}{((k-1)! * (n-k-1)!)} * \frac{n}{k * (n-k)}$$

$$= \left[ \frac{(n-1)!}{((k-1)! * (n-k-1)!)} \right] * \left[ \frac{1}{(n-k)} + \frac{1}{k} \right]$$

$$= \frac{(n-1)!}{((k-1)! * (n-k)!)} + \frac{(n-1)!}{(k! * (n-k-1)!)}$$

$$= \begin{pmatrix} n-1 \\ k-1 \end{pmatrix} + \begin{pmatrix} n-1 \\ k \end{pmatrix}$$

### Binomial Coefficient Using Decrease/Divide-and-Conquer

#### Pseudo-code

- Problem: Compute the binomial coefficient.
- ▶ Inputs: nonnegative integers n and k, where  $0 \le k \le n$ .
- **Outputs:** bin, the binomial coefficient  $\binom{n}{k}$

```
1: procedure BIN1(integer n, integer k)
      if (k = 0 \mid | n = k) then
          return 1
```

else

**return** bin(n-1, k-1) + bin(n-1, k) Recursive Cases

end if

7: end procedure

#### Complexity Analysis

- The algorithm is easy to design, but not efficient.
- reason-1: The divide-and-conquer approach is always inefficient when an instance is divided into two smaller instances that are almost as large as the original instance.
- reason-2: The same instances are solved in each recursive call.
- ▶ To determine  $\binom{n}{k}$ ,  $2\binom{n}{k} 1$  terms are computed.

> compute binomial coefficient

▶ Base Cases

#### Proof through mathematical induction

induction base: Show that for  $n = 1, 2 \binom{n}{k} - 1$  is true

$$2\begin{pmatrix} n \\ k \end{pmatrix} - 1 = 2\begin{pmatrix} 1 \\ 1 \end{pmatrix} - 1 = 2 - 1 = 1$$

- induction hypothesis : Assume that the number of terms needed to compute  $\binom{n}{k}$  are  $2\binom{n}{k}-1$
- induction step: Prove that the number of terms needed to compute  $\binom{n+1}{k}$  are  $2\binom{n+1}{k}-1$
- By the property of binomial coefficient

$$\left(\begin{array}{c} n+1 \\ k \end{array}\right) = \left(\begin{array}{c} n \\ k-1 \end{array}\right) + \left(\begin{array}{c} n \\ k \end{array}\right) + 1$$

So, by putting

$$\begin{pmatrix} n \\ k-1 \end{pmatrix} = 2 \begin{pmatrix} n \\ k-1 \end{pmatrix} - 1, \begin{pmatrix} n \\ k \end{pmatrix} = 2 \begin{pmatrix} n \\ k \end{pmatrix} - 1$$
 in above equation. 
$$\begin{pmatrix} n+1 \\ k \end{pmatrix} = 2 \begin{pmatrix} n \\ k-1 \end{pmatrix} - 1 + 2 \begin{pmatrix} n \\ k \end{pmatrix} - 1 + 1$$
 
$$= 2 \left[ \frac{n!}{(k-1)! (n-k-1)!} + \frac{n!}{(k)! (n-k)!} \right] - 1$$
 
$$= 2 \left[ \frac{n! (k+n-k+1)}{(k)! (n+1-k)!} \right] - 1$$
 
$$= 2 \left[ \frac{n! (n+1)}{(k)! (n+1-k)!} \right] - 1$$
 
$$= 2 \left[ \frac{(n+1)!}{(k)! (n+1-k)!} \right] - 1$$
 
$$= 2 \begin{pmatrix} n+1 \\ k \end{pmatrix} - 1$$

### **Binomial Coefficient Using Dynamic Programming**

```
    Algorithm

    1: procedure BC(n, k)
           integer i, i
           integer B[0..n][0..k]
           for (i = 0; i \le n; i + +) do
               for (i = 0; i \le min(i, k); i + +) do
                    if (i == 0 || i == i) then
                        B[i][i] = 1
                                                                                    i \quad B[i][j] = \begin{cases} B[i-1][j-1] + B[i-1][j], & 0 < j < i \\ 1, & j = 0 \text{ or } j = i \end{cases}
                    else
                         B[i[j] = B[i-1][j-1] + B[i-1][j]
                    end if
   10:
                end for
   11.
            end for
   12.
   13: end procedure
```

• Time complexity function : 
$$T(n,k) = T_1(n,k) + T_2(n,k) \in \Theta(nk)$$
  
 $T_1(n,k) = \sum_{i=1}^k \sum_{j=1}^i 1 = \sum_{i=1}^k i = \frac{k(k+1)}{2}, (i \le k)$   $T_2(n,k) = \sum_{i=k+1}^{n+1} \sum_{j=1}^{k+1} 1 = (n-k+1)(k+1), (i > k)$ 

- Solve the problem in bottom up fashion. It means that first compute the lowest/base value
- To compute  $B\begin{bmatrix} 4 \end{bmatrix}\begin{bmatrix} 2 \end{bmatrix} = \begin{pmatrix} 4 \\ 2 \end{pmatrix}$  row wise computing entries of matrix B.
  - ► Row 0:

$$B[0][0] = 1$$

► Row 1:

$$B[1][0] = 1$$
  
 $B[1][0] = 1$ 

► Row 2:

$$B[2][0] = 1$$
  
 $B[2][1] = B[1][0] + B[1][1] = 1 + 1 = 2$   
 $B[2][2] = 1$ 

• Row 3:

$$B[3][0] = 1$$
  
 $B[3][1] = B[2][0] + B[2][1] = 1 + 2 = 3$   
 $B[3][2] = B[2][1] + B[2][2] = 2 + 1 = 3$   
 $B[3][3] = 1$ 

• Row 4:

$$B [4] [0] = 1$$

$$B [4] [1] = B [3] [0] + B [3] [1] = 1 + 3 = 4$$

$$B [4] [2] = B [3] [1] + B [3] [2] = 3 + 3 = 6$$

$$B [4] [3] = B [3] [2] + B [3] [3] = 3 + 1 = 4$$

$$B [4] [4] = 1$$

### PATH COUNTING PROBLEM

### Path Counting Problem:

- A chess rook can move horizontally or vertically to any square in the same row or in the same column of a chessboard.
- Find the number of shortest paths by which a rook can move from one corner of a chessboard to the diagonally opposite corner.
- The length of a path is measured by the number of squares it passes through, including the first and the last squares.



#### Observations

- Let T(i,j) be the number of the rook's shortest paths from square (1,1) to square (i,j) in the ith row and the jth column, where  $1 \le i,j \le 8$
- base case: T(i,1) = P(1,j) = 1 for any  $1 \le i,j \le 8$ .

### PATH COUNTING PROBLEM (CONT...)

- recursive case : Any shortest path T(i,j) to square (i,j) is reached either from its left neighbor (i-1,j) or from its upper neighbors (i,j-1).
- Recursive Property

$$T [n] [m] = \begin{cases} T [i] [0] = 1, & j = 0 \\ T [0] [j] = 1, & i = 0 \\ T [i] [j] = T [i-1] [j] + T [i] [j-1] & 1 < i \le n, 1 < j \le m \end{cases}$$

- Using this recurrence, we can compute the values of T(i,j) for each square (i,j) of the board.
- This can be done either row by row, or column by column, or diagonal by diagonal.

#### TABLE 1: Number of Paths

1	1	1	1	1	1	1	1
1	2	3	4	5	6	7	8
1	3	6	10	15	21	28	36
1	4	10	20	35	56	84	120
1	5	15	35	70	126	210	330
1	6	21	56	126	252	462	792
1	7	28	84	210	462	924	1716
1	8	36	120	330	792	1716	3432

### PATH COUNTING PROBLEM (CONT...)

#### Divide/decrease and conquer based solution

```
1: procedure COUNTPATHDC(n,m)
     if (n == 1 || m == 1) then
        return 1
     else
        return (countPathDC(n-1,m) +
  countPathDC(n,m-1))
     end if
7: end procedure
```

### Complexity

$$\begin{split} \mathcal{T}\left(\textit{n},\textit{m}\right) &= \begin{cases} 1 & \textit{n} = 0, \textit{m} = 0 \\ \mathcal{T}\left(\textit{n} - 1, \textit{m}\right) + \mathcal{T}\left(\textit{n}, \textit{m} - 1\right) & \textit{n} > 0, \textit{m} > 0 \end{cases} \\ &\in \mathcal{O}(2^{\textit{max}\{\textit{m},\textit{n}\}}) \end{split}$$

### Dynamic programming based algorithm

```
1: procedure COUNTPATHDP(n,m)
       T[n][m]
       for (int i = 0; i < n; i++) do
          T[i][0] = 1
       end for
       for (int j = 0; j < m; i++) do
          T[0][i] = 1
       end for
       for (int i = 1; i < n; i++) do
          for (int i = 1; i < m; i++) do
10.
              T[i][i] = T[i-1][i] + T[i][i-1]
11:
          end for
       end for
13.
14: end procedure
Complexity
```

$$T(n,m) = n + m + nm \in \Theta(nm)$$

# PATH COUNTING PROBLEM (CONT...)

#### Permutations and Combinations

- Combinatorics:, Permutations → all possible ways of doing something, (lists).
  - Number of permutations of an n-element set: P(n) = n!
  - having n-elements and want to find the number of ways k items can be ordered:  $P(n,k) = \frac{n!}{(n-k)!}$
- Combinations (groups)
  - Number of k-combinations of an n-element set:

$$\begin{pmatrix} n \\ k \end{pmatrix} = \frac{P(n,k)}{k!} = \frac{n!}{k!(n-k)!}$$

- Number of subsets of an n-element set:  $2^n$
- Combinatorics formulae can be used to calculate the number of unique paths to reach destination cells starting from the cell(1,1). If there is lattice of size  $n \times m$  then paths from (1,1) to (n,m) are given as

$$paths = \frac{n!}{m!(n-m)!}$$

- procedure COUNTPATHCMN(n,m) paths=1
   for (i=n; i< m+n-1; i++) do</li>
   paths = paths × i
   paths = paths/i
   end for
   return paths
   end procedure
- Complexity

$$T(m,n) = \sum_{i=n}^{m+n-1} 1 = \sum_{i=1}^{m} 1 \in O(m)$$

$$\begin{pmatrix} 14 \\ 7 \end{pmatrix} = \frac{14!}{7!(14-7)!} = 3432$$

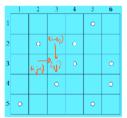
### Coin-collecting problem

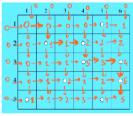
### Coin-collecting problem

- Several coins are placed in cells of an  $n \times m$  board, no more than one coin per cell
- A robot, located in the upper left cell of the board, needs The recursive property for computing F(i,j): to collect as many of the coins as possible and bring them to the bottom right cell.
- On each step, the robot can move either one cell to the right or one cell down from its current location.
- Solution
- Let F(i,j) be the largest number of coins the robot can collect and bring to the cell (i, j ) in the ith row and jth column of the board
- When the robot visits a cell with a coin, it always picks up that coin
- It can reach this cell either from the adjacent cell (i-1, j) above it or from the adjacent cell (i, j-1) to the left of it.
- The largest number of coins the robot can bring to cell (i,

- i) is the maximum of the two numbers F(i-1, j) and F(i, i-1), plus the one possible coin at cell (i, i) itself  $c_{ii}$ .

$$\left\{ \begin{array}{l} F\left(0,j\right) = 0, \; \text{for} \; 1 \leq j \leq m \\ F\left(i,0\right) = 0, \; \text{for} \; 1 \leq i \leq n \\ F\left(i,j\right) = \max \left\{ F\left(i-1,j\right) + c_{ij}, F\left(i,j-1\right) + c_{ij} \right\} \\ \text{for} \; 1 \leq i \leq n \quad \text{and} \; 1 \leq j \leq m \end{array} \right.$$





# Coin-collecting problem (cont...)

### **Algorithm**

- ▶ **Problem:** Apply dynamic programming to compute the largest number of coins a robot can collect on an  $n \times m$  board by starting at (1, 1) and moving right and down from upper left to down right corner
- ▶ Input: Matrix C [n, m] whose elements are equal to 1 and 0 for cells with and without a coin, respectively
- Output: Largest number of coins the robot can bring to cell (n, m)

### Algorithm (Complexity Analysis)

$$T(n,m) = \sum_{j=2}^{m} 1 + \sum_{i=2}^{n} \sum_{j=2}^{m} 1$$

$$= m - 1 + \sum_{i=2}^{n} (m-1)$$

$$= m - 1 + (m-1)(n-1)$$

$$= m - 1 + mn - m - n + 1$$

$$= mn - n + 2$$

#### Pseudo-code

```
1: procedure ROBOTCOINCOLLECTION(C[1...n, 1...m])
      F[1,1] = C[1,1]
      for (i = 2; i \le m; i + +) do
          F[1, j] = F[1, j - 1] + C[1, j]
      end for
      for (i = 2; <= n; i + +) do
          F[i, 1] = F[i, 1] + C[i, 1]
         for (i = 2; i <= m; j + +) do
             F[i,i] =
   \max \{F[i-1,j] + C[i,j], F[i,i-1] + C[i,i]\}
          end for
10:
      end for
11:
12: end procedure
                   T(n,m) \in \Theta(nm)
```

# Coin-collecting problem (cont...)

Optimal Path

 It is possible to trace the computations backwards to get an optimal path.

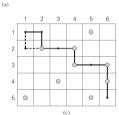
 If F(i-1, j) > F(i, j-1), an optimal path to cell (i, j) must come down from the adjacent cell above it;

• If F(i-1, j) < F(i, j-1), an optimal path to cell (i, j) must come from the adjacent cell on the left;

 If F(i-1, j) = F(i, j-1), it can reach cell (i, j) from either direction.

	1	2	3	4	5	6	
1					0		
2		0		0			
3				0		0	
4			0			0	
5	0				0		

1	2	3	4	5	6				
0	0	0	0	1	1				
0	1	1	2	2	2				
0	1	1	3	3	4				
0	1	2	3	3	5				
1	1	2	3	4	5				
(h)									



•

• Figures: (a) Coins to collect. (b) Dynamic programming algorithm results. (c) Two paths to collect 5 coins, the maximum number of coins possible.

### CHAINED MATRIX MULTIPLICATION

#### Problem definition

• Suppose we want to multiply a  $2 \times 3$  matrix with a  $3 \times 4$  matrix

$$\underbrace{\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}}_{2 \times 3} \times \underbrace{\begin{bmatrix} 7 & 8 & 9 & 1 \\ 2 & 3 & 4 & 5 \\ 6 & 7 & 8 & 9 \end{bmatrix}}_{3 \times 4} = \underbrace{\begin{bmatrix} 29 & 35 & 41 & 38 \\ 74 & 89 & 104 & 83 \end{bmatrix}}_{2 \times 4}$$

- Total entries in the resultant matrix are  $2 \times 4 = 8$ .
- The number of multiplication operation in one entry are  $=\underbrace{1\times7+2\times2+3\times6}_{3\ multiplications}=29$
- The number of multiplication in  $2 \times 4 = 8$  entries are  $= 2 \times 4 \times 3 = 24$ .
- In general, to multiply  $A_{i \times j}$  matrix with  $B_{j \times k}$  matrix using the standard method, the required number of multiplications are .

$$i \times j \times k$$

• Example: Consider the multiplication of the following four matrices:

$$A_{20\times2} \times B_{2\times30} \times C_{30\times12} \times D_{12\times8}$$

• For different order of matrices multiplications, the number of elementary multiplications are changed.

$$A(B(CD)) = 30 \times 12 \times 8 + 2 \times 30 \times 8 + 20 \times 2 \times 8$$

$$(AB)(CD) = 20 \times 2 \times 30 + 30 \times 12 \times 8 + 20 \times 30 \times 8$$

$$A((BC)D) = 2 \times 30 \times 12 + 2 \times 12 \times 8 + 20 \times 2 \times 8$$

$$= 8,880$$

$$A((BC)D) = 20 \times 2 \times 30 + 20 \times 30 \times 12 + 20 \times 12 \times 8$$

$$= 1,232$$

$$(A(BC))D = 2 \times 30 \times 12 + 20 \times 2 \times 12 \times 8$$

$$= 3,120$$

- Our goal is to develop an algorithm that determines the optimal order for multiplying n matrices.
- The optimal order depends only on the dimensions of the matrices.
- Therefore, besides n (number of matrices), these dimensions would be the only input to the algorithm

### **Recursive Solution**



### Algorithm

```
1: procedure MCMREC( dims[], i, j)
       cost = 0, minmul = inf
      if i \le i + 1 then
          return ()
      end if
      for k = i + 1: k < i: k + + do
          cost = cost + MCMRec(dims, i, k)
7:
          cost = cost + MCMRec(dims, k, j)
          cost = cost + dims[i] * dims[k] * dims[i]
          if cost < minmul then
10:
              minmul = cost
11.
          end if
12:
      end for
13.
      return minmul
14.
15: end procedure
```

- The brute-force algorithm is to consider all possible orders and take the minimum
- If we have just 1 item, then there is only one way to

parenthesize.

- If we have n items, then there are n-1 places where you could break the list with the outermost pair of parentheses
- Complexity
  - ▶ The number of different ways of parenthesizing n items is

$$\left\{ \begin{array}{ll} P(n) = 1, & n = 1 \\ P(n) = \sum\limits_{k = 1}^{n - 1} P(k)P(n - k), & n > 1 \end{array} \right.$$

Solution

$$P(n) \in \Omega\left(\frac{4^n}{n^{2/3}}\right)$$

- This is related to a famous function in combinatorics called the Catalan numbers.
- Catalan numbers are related to the number of different binary trees on n nodes.
- Catalan numbers are given by the formula:

$$C(n) = \frac{1}{n+1} \left( \begin{array}{c} 2n \\ n \end{array} \right)$$

### **Dynamic Programming Approach**

- let n matrices:  $\{A_1, A_2, \cdots, A_k, \cdots, A_n\}$  are given for multiplication
- principle of optimality applies in this problem. That is, the optimal order for multiplying n matrices includes the optimal order for multiplying any subset of the n matrices.
- For example, if the optimal order for multiplying six particular matrices is

$$A_1((((A_2A_3)A_4)A_5)A_6)$$

Then any subset  $(A_2A_3) A_4$  or  $((A_2A_3) A_4) A_5$  must be the optimal order for multiplying matrices

 If A<sub>k-1</sub> and A<sub>k</sub> matrices are multiplied then the number of columns in A<sub>k-1</sub> must equal the number of rows in A<sub>k</sub>.

 If let d<sub>k-1</sub> be the number of columns in A<sub>k-1</sub> and d<sub>k</sub> be the number of rows in A<sub>k</sub> for 1 ≤ k ≤ n, the dimension of A<sub>k</sub> is d<sub>k-1</sub> × d<sub>k</sub>, as shown in the Figure 1.

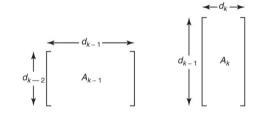


FIGURE 1: The number of columns in  $A_{k-1}$  is the same as the number of rows in  $A_k$ 

• Based on this observation, the following recursive property can be established when multiplying n matrices. for 1 < i < j < n

$$\left\{ \begin{array}{l} M\left[i\right]\left[j\right] = \displaystyle \mathop{\mathrm{minimum}}_{i \leq k \leq j-1} \left( M\left[i\right]\left[k\right] + M\left[k+1\right]\left[j\right] + d_{i-1}d_kd_j \right) \;, \;\; \textit{if} \;\; i < j \\ M\left[i\right]\left[i\right] = 0, \;\; \textit{otherwise} \end{array} \right.$$

### **Algorithm: Minimum Multiplications**

- Problem: Determining the minimum number of elementary multiplications needed to multiply n matrices and an order that produces that minimum number.
- Inputs: the number of matrices n, and an array of integers d, indexed from 0 to n, where d [i 1] × d [i] is the dimension of the i<sup>th</sup> matrix.
- Output: minmult, the minimum number of elementary multiplications needed to multiply the n matrices; a two-dimensional array P from which the optimal order can be obtained. P has its rows indexed from 1 to n-1 and its columns indexed from 1 to n. P[i][j] is the point where matrices i through j are split in an optimal order for multiplying the matrices.

#### Pseudo-code

```
1: procedure MINMULT(integer n,integer d[], integer P[][])
       integer i, j, k, diagonal
                                                                                 \triangleright variables i, j, k, diagonal of type integer
       integer M[1..n][1..n]
                                                                                    \triangleright an array M[1..n][1..n] of type integer
       for (i = 1; i <= n; i + +) do
           M[i][i] = 0
                                                                                                                 ▶ Base-case
       end for
       for (diagonal = 1; diagonal <= n - 1; diagonal + +) do
                                                                                7:
           for (i = 1; i \le n - diagonal; i + +) do
8.
              i = i + diagonal
               M[i][j] = \underset{i \le k \le i-1}{minimum} (M[i][k] + M[k+1][j] + d[i-1] * d[k] * d[j])
10:
               P[i][j] = k
                                                                                     \triangleright a value of k that gave the minimum
11.
           end for
12:
13:
       end for
       return M[1][n]
14:
15: end procedure
```

Note that, matrices themselves are not inputs because the values in the matrices are irrelevant to the problem

• Example: Consider the Problem Instance:

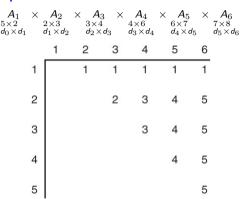


FIGURE 2: The matrix P

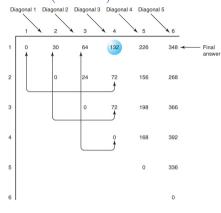


FIGURE 3: The matrix M

• The matrices M and P obtained by using the above algorithm are shown. Upper right corner provide the results. The matrix P produced by the algorithm can be used to print the optimal order

- The steps in the dynamic programming algorithm follow
  - ► Compute diagonal 0

$$M[i][i] = 0$$
 for  $1 \le i \le 6$ 

Compute diagonal 1

$$M[1][2] = \underbrace{\mininimum}_{1 \le k \le 1} (M[1][k] + M[k+1][2] + d_{i-1}d_kd_j)$$

$$= M[1][1] + M[2][2] + d_0d_1d_2$$

$$= 0 + 0 + (5 \times 2 \times 3) = 30$$

► Compute first element of diagonal 2 M[1][2]

► Compute first element of diagonal 3 M[1][3]



$$M \begin{bmatrix} 1 \end{bmatrix} \begin{bmatrix} 4 \end{bmatrix} = \underbrace{minimum}_{1 \le k \le 3} (M \begin{bmatrix} 1 \end{bmatrix} \begin{bmatrix} k \end{bmatrix} + M \begin{bmatrix} k+1 \end{bmatrix} \begin{bmatrix} 2 \end{bmatrix} + d_{i-1}d_kd_j)$$

$$= \min \begin{bmatrix} M \begin{bmatrix} 1 \end{bmatrix} \begin{bmatrix} 1 \end{bmatrix} + M \begin{bmatrix} 2 \end{bmatrix} \begin{bmatrix} 4 \end{bmatrix} + d_0d_1d_4, \\ M \begin{bmatrix} 1 \end{bmatrix} \begin{bmatrix} 2 \end{bmatrix} + M \begin{bmatrix} 3 \end{bmatrix} \begin{bmatrix} 4 \end{bmatrix} + d_0d_2d_4, \\ M \begin{bmatrix} 1 \end{bmatrix} \begin{bmatrix} 3 \end{bmatrix} + M \begin{bmatrix} 4 \end{bmatrix} \begin{bmatrix} 4 \end{bmatrix} + d_0d_3d_4 \end{bmatrix}$$

$$= \min \begin{bmatrix} 0 + 72 + (5 \times 2 \times 6), \\ 30 + 72 + (5 \times 3 \times 6), \\ 64 + 0 + (5 \times 4 \times 6) \end{bmatrix}$$

$$= 132$$

- ► Compute first element of diagonal 4 → M[1][4]
- ightharpoonup Compute first element of diagonal 5  $\rightarrow$  M[1][5]
- ightharpoonup Compute first element of diagonal 6  $\rightarrow$  M[1][6]
- ► Similarly, compute other entries of the resultant matrix

#### Complexity Function

$$T(n) = \sum_{d=1}^{n-1} \sum_{i=1}^{n-d} \sum_{k=i}^{j-1} 1$$

$$= \sum_{d=1}^{n-1} nd - \sum_{d=1}^{n-1} d^{2}$$

$$= \sum_{d=1}^{n-1} nd - \sum_{d=1}^{n-1} d^{2}$$

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

$$= \sum_{d=1}^{n-1} \sum_{i=1}^{n-d} (j-1-i+1)$$

$$= \sum_{d=1}^{n-1} \sum_{i=1}^{n-d} (i+d-1-i+1)$$

$$= \sum_{d=1}^{n-1} \sum_{i=1}^{n-d} d$$

$$= \sum_{d=1}^{n-1} \sum_{i=1}^{n-d} d$$

$$= \sum_{d=1}^{n-1} (n-d) \times d$$

where  $j = i+d$ 

$$= \sum_{d=1}^{n-1} nd - \sum_{d=1}^{n-1} d^{2}$$

$$= \frac{n^{3}-n^{2}}{2} - \frac{2n^{3}-3n^{2}+n}{6}$$

$$= \frac{3n^{3}-3n^{2}-2n^{3}+3n^{2}-n}{6}$$

$$= \frac{n^{3}-n}{6}$$

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

Hence

$$T(n) \in \Theta(n^3)$$

#### Algorithm: Print Optimal Order

- **Problem:** Print the optimal order for multiplying *n* matrices.
- Inputs: Positive integer n, and the array P produced by Algorithm 3.6. P[i][j] is the point where matrices i through j are split in an optimal order for multiplying those matrices.
- Outputs: the optimal order for multiplying the matrices.

#### Pseudo-code

```
1: procedure ORDER(integer i, integer j)
2: if (i == j) then
3: print(A, i)
4: else
5: k = P[i][j]
6: print((i)
7: order(i, k)
8: order(k + 1, j)
9: print((i)
10: end if
11: end procedure
```

Complexity in asymptotic notations

$$T(n) \in \Theta(n)$$

- Remarks
  - ▶ The presented  $\Theta$  ( $n^3$ ) algorithm for chained matrix multiplication is from Godbole (1973).
  - ▶ Yao (1982) developed methods for speeding up certain dynamic programming solutions. Using those methods, it is possible to create a  $\Theta\left(n^2\right)$  algorithm for chained matrix multiplication.
  - ▶ Hu and Shing (1982, 1984) describe a  $\Theta(n \lg n)$  algorithm for chained matrix multiplication.

### OPTIMAL BINARY SEARCH TREE

#### **Binary Search Tree**

- A binary search tree is a binary tree of items (called keys), that come from an ordered set, such that
  - Each node contains one key.
  - The keys in the left subtree of a given node are less than or equal to the key in that node.
  - ► The keys in the **right subtree** of a given node are greater than or equal to the key in that node.
- The depth/height of a node in a tree is the number of edges in the unique path from the root to the node. It is also called the level of the node in the tree

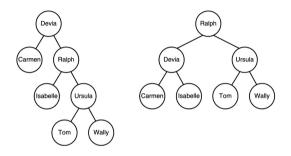


FIGURE 4: Two binary search trees

- A binary tree is called balanced tree if the depth of the two subtrees of every node never differ by more than 1
- The tree on the left in Figure 4 is not balanced, whereas the tree on the right in Figure 4 is balanced.
- An algorithm that searches for a key in a binary search tree is provided here

#### Algorithm: Searching Binary Tree

- Problem: Determine the node containing a key in a binary search tree. It is assumed that the key is in the tree.
- ▶ Inputs: A pointer tree to a binary search tree and a key keyin.
- **Outputs:** a pointer p to the node containing the key.

#### Pseudo-code

```
1: procedure SEARCH(Tree, keyin)
       bool found = false
                                                                                              ▷ Boolean variable found
       while (!found) do
          if (p- > key == keyin) then
5.
              found = true
          else
6:
7:
              if (keyin  key) then
                 p = p - > left
                                                                                            > advance to the left child
              else
                 p = p - > right

    ▷ advance to the right child

10.
              end if
11:
          end if
12:
       end while
13:
       return p
14:
15: end procedure
```

#### Optimal Binary Search Tree

- Our goal is to organize the keys in a binary search tree so that the average time it takes to locate a key is minimized.
- Let  $k_1, k_2, ..., k_n$  be keys and their probabilities be  $p_1, p_2, ..., p_n$
- Search time (number of comparisons) for ith key  $time(k_i) = depth(k_i) + 1$

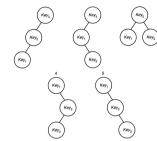
Average Time 
$$= \sum_{i=1}^{n} time(k_i)p_i$$

$$= \sum_{i=1}^{n} (depth(k_i) + 1)p_i$$

$$= \sum_{i=1}^{n} (depth(k_i))p_i + \sum_{i=1}^{n} p_i$$

$$= \sum_{i=1}^{n} (depth(k_i))p_i + 1$$

• Example: five different trees are shown when n=3 and probability for each item  $p_1=0.7,\ p_2=0.2,\ p_3=0.1$ 



• The average search times for the trees in Figure are:

$$\begin{array}{l} 3 (0.7) + 2 (0.2) + 1 (0.1) = 2.6 \\ 2 (0.7) + 3 (0.2) + 1 (0.1) = 2.1 \\ 2 (0.7) + 1 (0.2) + 2 (0.1) = 1.8 \\ 1 (0.7) + 3 (0.2) + 2 (0.1) = 1.5 \\ 1 (0.7) + 2 (0.2) + 3 (0.1) = 1.4 \end{array}$$

- Let  $key_1, key_2, key_3, \dots, key_n$  be the n keys in order, and let  $p_i$  be the probability that  $key_i$  is the search key.
- The number of binary search trees with n keys are given by  $\frac{1}{(n+1)}\left(\begin{array}{c}2n\\n\end{array}\right)$
- We will call a tree optimal for those keys with minim average time(AST) for searching and denote the ASt values by A[i][j].
- It takes one comparison to locate a key in a tree containing one key,  $A[i][i] = p_i$ .
- let tree 1 be an optimal tree given the restriction that key1 is at the root, tree 2 be an optimal tree given the restriction that key2 is at the root, ..., tree n be an optimal tree given the restriction that keyn is at the root.

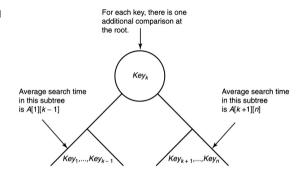


FIGURE 5: Optimal binary search tree given that  $key_k$  is at the root.

• For  $1 \le k \le n$ , the subtrees of tree k must be optimal. The average search times in these subtrees are as depicted in Figure .

#### Average search time

$$\frac{\mathcal{A}\left[1\right]\left[k-1\right]}{\text{Average time in left subtree}} + \underbrace{p_1 + \dots + p_{k-1}}_{\text{Additional time comparaing at root}} + \underbrace{p_k}_{\text{Average time serching for root}} + \underbrace{\mathcal{A}\left[k+1\right]\left[n\right]}_{\text{Average time in right subtree}} + \underbrace{p_{k+1} + \dots + p_n}_{\text{Additional time comparaing at root}}$$

$$\Rightarrow \mathcal{A}\left[1\right]\left[k-1\right] + \mathcal{A}\left[k+1\right]\left[n\right] + \sum_{m=1}^{n} p_m$$

#### The recursive property

$$\left\{
\begin{array}{l}
A\left[i\right]\left[j\right] = 0, & i > j \\
A\left[i\right]\left[i\right] = 0, & i = j
\end{array}\right\} \rightarrow (\text{Base Cases})$$

$$A\left[i\right]\left[j\right] = \underset{i \le k \le j}{\text{minimum}} \left(A\left[i\right]\left[k-1\right] + A\left[k+1\right]\left[j\right]\right) + \underset{m=i}{\overset{j}{\sum}} p_m \rightarrow (\text{Recursive Cases})$$

- Algorithm Optimal Binary Search Tree Dynamic programming will be used to develop a more efficient algorithm.
  - ▶ Problem: Determine an optimal binary search tree for a set of keys, each with a given probability of being the search key.
  - ▶ Inputs: n, the number of keys, and an array of real numbers p indexed from 1 to n, where p [i] is the probability of searching for the ith key.
  - ▶ Outputs: A variable minavg, whose value is the average search time for an optimal binary search tree; and a two-dimensional array R from which an optimal tree can be constructed. R has its rows indexed from 1 to n + 1 and its columns indexed from 0 to n. R [i] [j] is the index of the key in the root of an optimal tree containing the ith through the jth keys.

#### Pseudo-code

```
1: procedure OPTSEARCHTREE(P[])
          for (i = 1; i \le n; i + +) do
             A[i][i-1] = 0, A[i][i] = 0
              R[i][i-1] = 0, R[i][i] = 0
          end for
          A[n+1][n] = 0, R[n+1][n] = 0
          for (diagonal = 1; diagonal <= n - 1; diagonal + +) do
               for (i = 1; i \le n - diagonal; i + +) do
                  i = i + diagonal
                  A[i][j] = \underset{i \leq k \leq j}{\operatorname{minimum}} (A[i][k-1] + A[k+1][j]) + \sum_{j=1}^{j} p_{m}
   10:
                   R[i][i] = k
   11:
               end for
   12:
           end for
   13:
           return minavg A[1][n]
   14:
   15: end procedure
• Complexity T(n) = \frac{n(n-1)(n+4)}{c} \in \Theta(n^3)
```

- Algorithm: Build Optimal Binary Search Tree
  - **Problem:** Build an optimal binary search tree.
  - ▶ Inputs: n, the number of keys, an array Key containing the n keys in order, and the array R produced by Algorithm 3.9.
    R[i][j] is the index of the key in the root of an optimal tree containing the ith through the jth keys.
  - Outputs: a pointer tree to an optimal binary search tree containing the n keys.
- Complexity  $T(n) \in \Theta(n)$

#### Pseudo-code

```
1: procedure TREE( R[][], i, j)
      Integer k = R[i][j]
      node-pointer p
      if (k == 0) then
          return null
5.
      else
6:
          p = new nodetvpe
          p- > key = Key[k]
          p- > left = tree(R[][], i, k-1)
          p- > right = tree(R[][], k+1, j)
10.
11:
          return p
      end if
12:
13: end procedure
```

 Example: Supposed we have the following values of the array Key:

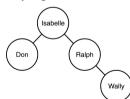
Don	Isabelle	Ralph	Wally
Key[1]	Key[2]	Key[3]	Key[4]

	0	1	2	3	4		0	1	2	3	4
1	0	3 8	9 8	11 8 5 8	7/4	1	0	1	1	2	
2		0	3	<u>5</u> 8	1	2		0	2	2	2
3			0	18	38	3			0	3	3
4				0	1/8	4				0	4
5					0	5					0
			Α						R		

• The tree created by Algorithm 3.10 are shown in Figure.

$$\mathbf{p} = \begin{bmatrix} 0.375 & 0.375 & 0.125 & 0.125 \end{bmatrix}$$

 $\bullet$  The matrices A and R produced by Algorithm 3.9 are shown in Figure. The minimal average search time is 7/4.



### More Problems....

#### More Problems....

- Rod-cutting problem: Design a dynamic programming algorithm for the following problem. Find the maximum total sale price that can be obtained by cutting a rod of n units long into integer-length pieces if the sale price of a piece i units long is pi for i=1,2,...,n.
- Longest path in a DAG: Design an efficient algorithm for finding the length of the longest path in a dag.

  This problem is important both as a prototype of many other dynamic programming applications and in its own right because it determines the minimal time needed for completing a project comprising precedence constrained tasks.
- Maximum square submatrix Given an  $m \times n$  boolean matrix B, find its largest square submatrix whose elements are all zeros.
  - The algorithm may be useful for, say, finding the largest free square area on a computer screen or for selecting a construction site.
- 0-1 Knapsack: Given objects  $x_1, \ldots, x_n$ , where object  $x_i$  has weight  $w_i$  and profit  $p_i$  (if its placed in the knapsack), determine the subset of objects to place in the knapsack in order to maximize profit, assuming that the sack has capacity M.

# More Problems.... (cont...)

- Longest Common Subsequence: Given an alphabet  $\Sigma$ , and two words X and Y whose letters belong to  $\Sigma$ , find the longest word Z which is a (non-contiguous) subsequence of both X and Y.
- blue All-Pairs Minimum Distance : Given a directed graph G = (V, E), find the distance between all pairs of vertices in V.
- Polygon Triangulation: Given a convex polygon  $P = \langle v_0, v_1, \dots, v_{n-1} \rangle$  and a weight function defined on both the chords and sides of P, find a triangulation of P that minimizes the sum of the weights of which forms the triangulation.
- Traveling Salesperson: given n cities  $c_1, \ldots, c_n$ , where  $c_i$  has grid coordinates  $(x_i, y_i)$ , and a cost matrix C, where entry  $C_{ij}$  denotes the cost of traveling from city i to city j, determine a left-to-right followed by right-to-left Hamilton-cycle tour of all the cities which minimizes the total traveling cost. In other words, the tour starts at the leftmost city, proceeds from left to right visiting a subset of the cities (including the rightmost city), and then concludes from right to left visiting the remaining cities.
- Viterbi's algorithm for context-dependent classification: Given a set of observations  $\vec{x}_1, \dots, \vec{x}_n$  find the sequence of classes  $\omega_1, \dots, \omega_n$  that are most likely to have produced the observation sequence.

# More Problems.... (cont...)

• Edit Distance: Given two words u and v over some alphabet, determine the least number of edits (letter deletions, additions, and changes) that are needed to transform u into v.

### SUMMARY

- COMPUTING BINOMIAL COEFFICIENTS
- PATH COUNTING PROBLEM
- Coin-collecting Problem
- O CHAINED MATRIX MULTIPLICATION
- **10** OPTIMAL BINARY SEARCH TREE