

***Matrix Chain Multiplication by Dynamic
Programming
Spring 2022***

Outline

- Review of matrix multiplication.
- The chain matrix multiplication problem.
- A **dynamic programming** algorithm for chain matrix multiplication.

Rules to multiply Two Matrices

The number of **columns of the 1st matrix** must equal the number of **rows of the 2nd matrix**.

And the result will have the same number of **rows as the 1st matrix**, and the same number of **columns as the 2nd matrix**.

The diagram shows the equation $(m \times n) \cdot (n \times k) = (m \times k)$. A blue curved arrow points from the n in the first matrix to the n in the second matrix, indicating they must be equal for the product to be defined. A purple curved arrow points from the n in the second matrix to the n in the result matrix, indicating the result inherits the number of columns from the second matrix. An orange curved arrow points from the k in the second matrix to the k in the result matrix, indicating the result inherits the number of rows from the second matrix. Below the equation, the text "product is defined" is written in purple.

$$(m \times n) \cdot (n \times k) = (m \times k)$$

product is defined

$$\begin{array}{c}
 \vec{a}_1 \rightarrow \\
 \vec{a}_2 \rightarrow
 \end{array}
 \begin{array}{c}
 A \\
 \left[\begin{array}{cc} 1 & 7 \\ 2 & 4 \end{array} \right]
 \end{array}
 \cdot
 \begin{array}{c}
 \vec{b}_1 \quad \vec{b}_2 \\
 \downarrow \quad \downarrow \\
 B \\
 \left[\begin{array}{cc} 3 & 3 \\ 5 & 2 \end{array} \right]
 \end{array}
 =
 \begin{array}{c}
 C \\
 \left[\begin{array}{cc}
 \vec{a}_1 \cdot \vec{b}_1 & \vec{a}_1 \cdot \vec{b}_2 \\
 \vec{a}_2 \cdot \vec{b}_1 & \vec{a}_2 \cdot \vec{b}_2
 \end{array} \right]
 \end{array}$$

Matrix Multiplication

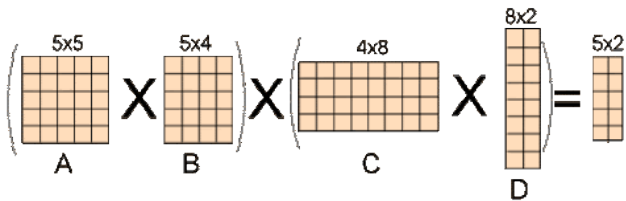
"Dot Product"

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} = \begin{bmatrix} 58 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} = \begin{bmatrix} 58 & 64 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} = \begin{bmatrix} 58 & 64 \\ 139 & 154 \end{bmatrix} \quad \checkmark$$

Matrix Multiplication



Review of Matrix Multiplication

Matrix: An $n \times m$ matrix $A = [a[i,j]]$ is a two-dimensional array

$$A = \begin{bmatrix} a[1,1] & a[1,2] & \cdots & a[1,m-1] & a[1,m] \\ a[2,1] & a[2,2] & \cdots & a[2,m-1] & a[2,m] \\ \vdots & \vdots & & \vdots & \vdots \\ a[n,1] & a[n,2] & \cdots & a[n,m-1] & a[n,m] \end{bmatrix},$$

which has n rows and m columns.

Example

A 4×5 matrix:

$$\begin{bmatrix} 12 & 8 & 9 & 7 & 6 \\ 7 & 6 & 89 & 56 & 2 \\ 5 & 5 & 6 & 9 & 10 \\ 8 & 6 & 0 & -8 & -1 \end{bmatrix}.$$

Review of Matrix Multiplication

The product $C = AB$ of a $p \times q$ matrix A and a $q \times r$ matrix B is a $p \times r$ matrix C given by

$$c[i,j] = \sum_{k=1}^q a[i,k]b[k,j], \quad \text{for } 1 \leq i \leq p \text{ and } 1 \leq j \leq r$$

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Example

$$A = \begin{bmatrix} 1 & 8 & 9 \\ 7 & 6 & -1 \\ 5 & 5 & 6 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 8 \\ 7 & 6 \\ 5 & 5 \end{bmatrix}, \quad C = AB = \begin{bmatrix} 102 & 101 \\ 44 & 87 \\ 70 & 100 \end{bmatrix}.$$

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Matrix multiplication is **NOT commutative**, e.g.,



$$A_1A_2 \neq A_2A_1$$

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Implication: Multiplication “sequence” (parenthesization) is important!!

Order of operations makes a huge difference. How do we compute the minimum?

Each parenthesization defines a set of **$n-1$** matrix multiplications. We just need to pick the parenthesization that corresponds to the best ordering.

Trying all possible parenthesizations is a bad idea!!!

- Review of matrix multiplication.
- The chain matrix multiplication problem.
- A [dynamic programming](#) algorithm for chain matrix multiplication.

The Chain Matrix Multiplication Problem

Definition (Chain matrix multiplication problem)

Given dimensions p_0, p_1, \dots, p_n , corresponding to matrix sequence A_1, A_2, \dots, A_n in which A_i has dimension $p_{i-1} \times p_i$, determine the “multiplication sequence” that minimizes the number of scalar multiplications in computing $A_1 A_2 \cdot \cdot \cdot A_n$.

- i.e., determine how to parenthesize the multiplications.

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Example

$$\begin{aligned} A_1 A_2 A_3 A_4 &= (A_1 A_2)(A_3 A_4) = A_1(A_2(A_3 A_4)) = A_1((A_2 A_3)A_4) \\ &= ((A_1 A_2)A_3)(A_4) = (A_1(A_2 A_3))(A_4) \end{aligned}$$

Exhaustive search: $\Omega(4^n/n^{3/2})$.

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Is there a better approach?

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Yes – DP

Developing a Dynamic Programming Algorithm

Step 1: Define Space of Subproblems

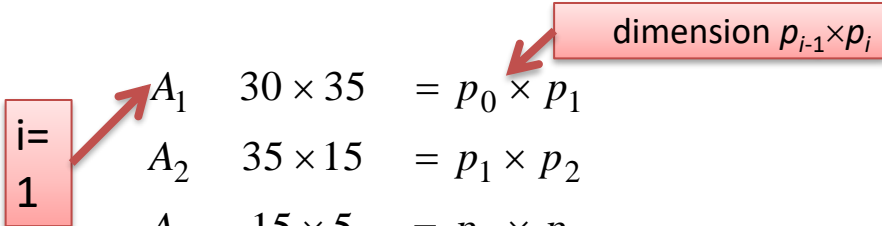
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 $A_{i..j} = A_i A_{i+1} \cdots A_j$.
 - Note that $A_{i..j}$ is a $p_{i-1} \times p_j$ matrix.

Example:



A_1	30×35	$= p_0 \times p_1$
A_2	35×15	$= p_1 \times p_2$
A_3	15×5	$= p_2 \times p_3$
A_4	5×10	$= p_3 \times p_4$
A_5	10×20	$= p_4 \times p_5$
A_6	20×25	$= p_5 \times p_6$

Given a chain A_1, A_2, \dots, A_n of n matrices, where for $i=1, 2, \dots, n$, matrix A_i has dimension $p_{i-1} \times p_i$

Note

*In the matrix-chain multiplication problem, **we are not actually multiplying matrices.***

*Our goal is only to **determine an order for multiplying matrices** that has the lowest cost.*

Typically, the time invested in determining this optimal order is more than paid for by the time saved later on when actually performing the matrix multiplications (such as performing only 7500 scalar multiplications instead of 75,000).

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Note that $A_{i..j}$ is a $p_{i-1} \times p_j$ matrix.
- There are $\Theta(n^2)$ such subproblems.(Why?)
- How can we solve larger problems using subproblem solutions?

Relationships among subproblems

At the last step of *any* optimal multiplication sequence (for a subproblem), there is some k such that the two matrices $A_{i..k}$ and $A_{k+1..j}$ are multiplied together.

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How do we parenthesize the two subchains $A_{i..k}$ and $A_{k+1..j}$?

ANS: $A_{i..k}$ and $A_{k+1..j}$ must be computed optimally, so we can apply the same procedure *recursively*.

If the “optimal” solution of $A_{i..j}$ involves splitting into $A_{i..k}$ and $A_{k+1..j}$ at the final step, then parenthesization of $A_{i..k}$ and $A_{k+1..j}$ in the optimal solution must also be optimal

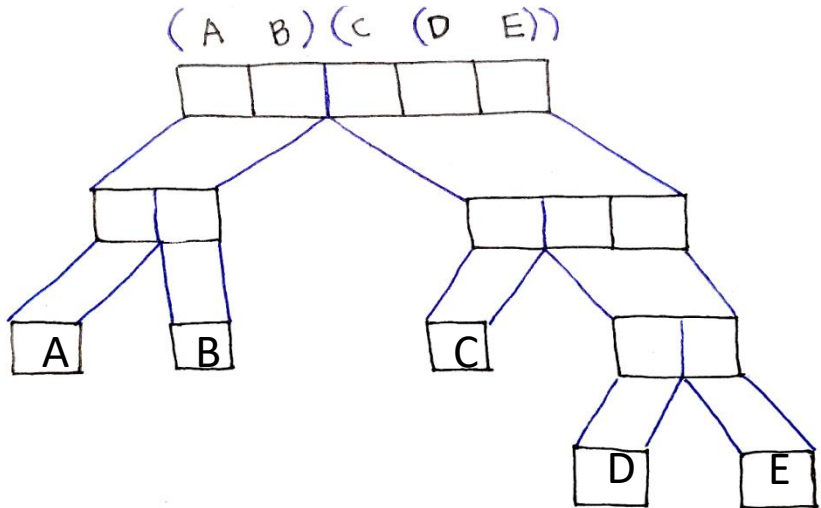
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- If parenthesization of $A_{i..k}$ was **not** optimal, it could be replaced by a cheaper parenthesization, yielding a cheaper final solution, contradicting optimality
- Similarly, if parenthesization of $A_{k+1..j}$ was **not** optimal, it could be replaced by a cheaper parenthesization, again yielding contradiction of cheaper final solution.

Dynamic Programming Approach



Step 2: Constructing optimal solutions from optimal subproblem solution

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For $1 \leq i \leq j \leq n$, let $m[i, j]$ denote the minimum number of multiplications needed to compute $A_{i..j}$. This **optimum cost** must satisfy the following recursive definition.

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$$m[i, j] = \begin{cases} 0 & i = j, \\ \min_{i \leq k < j} (m[i, k] + m[k + 1, j] + p_{i-1}p_kp_j) & i < j \end{cases}$$

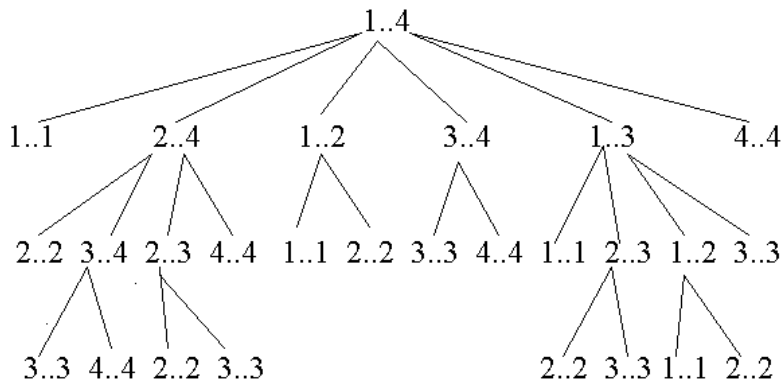
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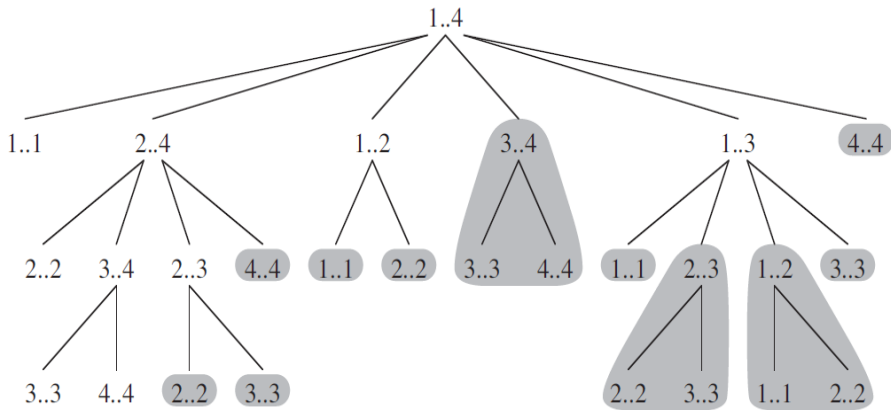
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Overlapping subproblems (contd.)



recursion tree for computation of `RECURSIVE-MATRIX-CHAIN(p1,4)`

Overlapping Sub-Problems



Developing a Dynamic Programming Algorithm

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An easy way to ensure this is to compute them in increasing order of the size $(j - i)$ of the matrix-chain $A_{i..j}$:

$m[1, 2], m[2, 3], m[3, 4], \dots, m[n - 3, n - 2], m[n - 2, n - 1], m[n - 1, n]$



Set of 2 Matrices

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Set of 3 Matrices

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Set of 4 Matrices

Developing a Dynamic Programming Algorithm

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...

$m[1, n - 1], m[2, n]$

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$m[1, n - 1], m[2, n]$

$m[1, n]$

Example for the Bottom-Up Computation

Example

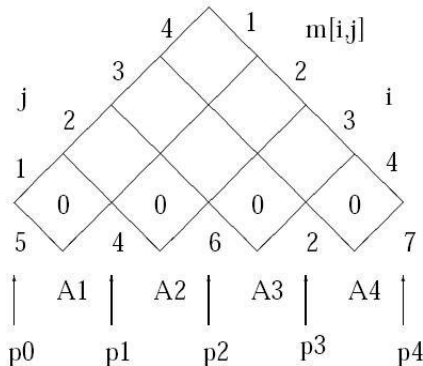
A chain of four matrices A_1, A_2, A_3 and A_4 , with $p_0 = 5, p_1 = 4, p_2 = 6, p_3 = 2$ and $p_4 = 7$. Find $m[1, 4]$.

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S0: Initialization



Example – Continued

$A_{15 \times 4}$, $A_{24 \times 6}$, $A_{36 \times 2}$, $A_{42 \times 7}$

Step 1: Computing $m[1, 2]$

	1	2	3	4
1	0			
2	NA	0		
3	NA	NA	0	
4	NA	NA	NA	0

$A_{15 \times 4}$

$A_{24 \times 6}$

$COST = 5 \times 4 \times 6 = 120$

$M[1, 2] = 120$

Example – Continued

$A_{15 \times 4}$, $A_{24 \times 6}$, $A_{36 \times 2}$, $A_{42 \times 7}$

Step 1: Computing $m[1, 2]$

	1	2	3	4
1	0	120		
2	NA	0		
3	NA	NA	0	
4	NA	NA	NA	0

$A_{15 \times 4}$

$A_{24 \times 6}$

$\text{COST} = 5 \times 4 \times 6 = 120$

$M[1, 2] = 120$

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[2,3]$

	1	2	3	4
1	0	120		
2	NA	0	48	
3	NA	NA	0	
4	NA	NA	NA	0

$A_{2 \times 6}$

$A_{3 \times 2}$

$\text{COST} = 4 \times 6 \times 2 = 48$

$M[2,3] = 48$

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[3,4]$

	1	2	3	4
1	0	120		
2	NA	0	48	
3	NA	NA	0	84
4	NA	NA	NA	0

$A_{3 \times 2}$

$A_{4 \times 7}$

$COST = 6 \times 2 \times 7 = 84$

$M[3,4] = 84$

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[1,3]$

	1	2	3	4
1	0	120		
2	NA	0	48	
3	NA	NA	0	84
4	NA	NA	NA	0

$A_1 \cdot (A_2 \cdot A_3)$ or $(A_1 \cdot A_2) \cdot A_3$

Two Possibilities to multiply 3 matrices

Example – Continued

$A_{15 \times 4}$, $A_{24 \times 6}$, $A_{36 \times 2}$, $A_{42 \times 7}$

Step 1: Computing $m[1,3]$

$A1. (A2 . A3)$ or $(A1. A2). A3$

$$\begin{aligned} &A_{15 \times 4}, (A_{24 \times 6}, A_{36 \times 2}) \\ &= m[1,1] + m[2,3] + 5 * 4 * 2 \\ &= 0 + 48 + 40 \\ &= 88 \end{aligned}$$

$$\begin{aligned} &(A_{15 \times 4} . A_{24 \times 6}) . A_{36 \times 2} \\ &= m[1,2] + m[3,3] + 5 * 6 * 2 \\ &= 120 + 0 + 60 \\ &= 180 \end{aligned}$$



Pick Minimum

Two Possibilities to multiply 3 matrices

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[1,3]$

	1	2	3	4
1	0	120	88	
2	NA	0	48	
3	NA	NA	0	84
4	NA	NA	NA	0

$A_1 \cdot (A_2 \cdot A_3)$ or $(A_1 \cdot A_2) \cdot A_3$

Two Possibilities to multiply 3 matrices

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[2, 4]$

	1	2	3	4
1	0	120	88	
2	NA	0	48	
3	NA	NA	0	84
4	NA	NA	NA	0

$A_2 \cdot (A_3 \cdot A_4)$ or $(A_2 \cdot A_3) \cdot A_4$

Two Possibilities to multiply 3 matrices

Example – Continued

$A_{15 \times 4}$, $A_{24 \times 6}$, $A_{36 \times 2}$, $A_{42 \times 7}$

Step 1: Computing $m[2,4]$

$A_2 . (A_3 . A_4)$ or $(A_2 . A_3) . A_4$

$$\begin{aligned} &A_{24 \times 6} . (A_{36 \times 2}, A_{42 \times 7}) \\ &= m[2,2] + m[3,4] + 4 \times 6 \times 7 \\ &= 0 + 84 + 168 \\ &= 252 \end{aligned}$$

$$\begin{aligned} &(A_{24 \times 6} . A_{36 \times 2}) . A_{42 \times 7} \\ &= m[1,2] + m[3,3] + 4 \times 2 \times 7 \\ &= 48 + 0 + 56 \\ &= 104 \end{aligned}$$

Pick Minimum

Two Possibilities to multiply 3 matrices

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[2,4]$

	1	2	3	4
1	0	120	88	
2	NA	0	48	104
3	NA	NA	0	84
4	NA	NA	NA	0

$A_1 \cdot (A_2 \cdot A_3)$ or $(A_1 \cdot A_2) \cdot A_3$

Two Possibilities to multiply 3 matrices

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[2,4]$

	1	2	3	4
1	0	120	88	
2	NA	0	48	104
3	NA	NA	0	84
4	NA	NA	NA	0

$A_1 \cdot (A_2 \cdot A_3 \cdot A_4)$ or $(A_1 \cdot A_2) \cdot (A_3 \cdot A_4)$ or
 $(A_1 \cdot A_2 \cdot A_3) \cdot A_4$

Three Possibilities

$A_{15 \times 4}$, $A_{24 \times 6}$, $A_{36 \times 2}$, $A_{42 \times 7}$

$A1. (A2 . A3. A4)$ or $(A1. A2). (A3 . A4)$ or
 $(A1 .A2. A3). A4$

$M[1,4] = m[1,1] + m[2,4] + 5 \times 4 \times 7,$
 $m[1,2] + m[3,4] + 5 \times 6 \times 7,$
 $m[1,3] + m[4,4] + 5 \times 2 \times 7$

$M[1,4] = 0 + 104 + 140,$
 $120 + 84 + 210,$
 $88 + 0 + 70$

Three Possibilities

$M[1,4] = 244,$
 $414,$
 158

Pick Minimum

Example – Continued

$A_{1 \times 4}$, $A_{2 \times 6}$, $A_{3 \times 2}$, $A_{4 \times 7}$

Step 1: Computing $m[1,4]$

	1	2	3	4
1	0	120	88	158
2	NA	0	48	104
3	NA	NA	0	84
4	NA	NA	NA	0

$A_1 \cdot (A_2 \cdot A_3 \cdot A_4)$ or $(A_1 \cdot A_2) \cdot (A_3 \cdot A_4)$ or
 $(A_1 \cdot A_2 \cdot A_3) \cdot A_4$

Three Possibilities

Example – Continued

$A_{15 \times 4}$, $A_{24 \times 6}$, $A_{36 \times 2}$, $A_{42 \times 7}$

Split point Matrix

S	1	2	3	4
1		1	1	3
2			2	3
3				3
4				

Example – Continued

Step 1: Computing $m[1, 2]$

By definition

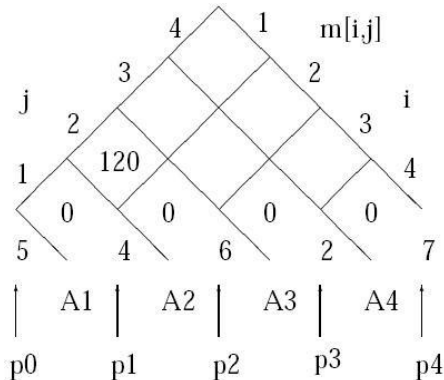
$$\begin{aligned} m[1, 2] &= \min_{1 \leq k < 2} (m[1, k] + m[k + 1, 2] + p_0 p_k p_2) \\ &= m[1, 1] + m[2, 2] + p_0 p_1 p_2 = 120. \end{aligned}$$

Example – Continued

Step 1: Computing $m[1, 2]$

By definition

$$\begin{aligned} m[1, 2] &= \min_{1 \leq k < 2} (m[1, k] + m[k + 1, 2] + p_0 p_k p_2) \\ &= m[1, 1] + m[2, 2] + p_0 p_1 p_2 = 120. \end{aligned}$$



Example – Continued

Step 2: Computing $m[2, 3]$

By definition

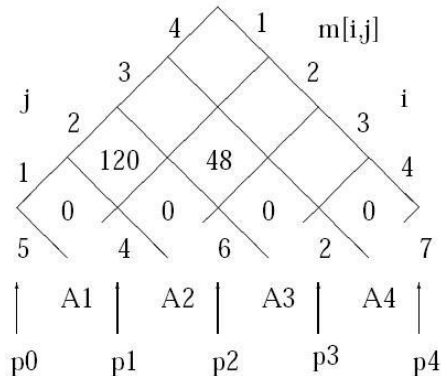
$$\begin{aligned} m[2, 3] &= \min_{2 \leq k < 3} (m[2, k] + p m[k + 1, 3] + p_1 p_k p_3) \\ &= m[2, 2] + m[3, 3] + p_1 p_2 p_3 = 48. \end{aligned}$$

Example – Continued

Step 2: Computing $m[2, 3]$

By definition

$$\begin{aligned} m[2,3] &= \min_{2 \leq k < 3} (m[2,k] + pm[k+1,3] + p_1 p_k p_3) \\ &= m[2,2] + m[3,3] + p_1 p_2 p_3 = 48. \end{aligned}$$



Example – Continued

Step 3: Computing $m[3, 4]$

By definition

$$m[3, 4] = \min_{3 \leq k < 4} (m[3, k] + m[k + 1, 4] + p_2 p_k p_4)$$

Example – Continued

Step 3: Computing $m[3, 4]$

By definition

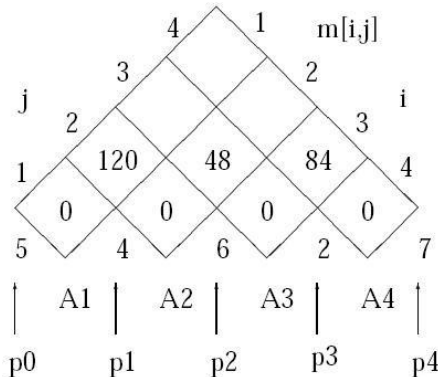
$$\begin{aligned} m[3, 4] &= \min_{3 \leq k < 4} (m[3, k] + m[k + 1, 4] + p_2 p_k p_4) \\ &= m[3, 3] + m[4, 4] + p_2 p_3 p_4 = 84. \end{aligned}$$

Example – Continued

Step 3: Computing $m[3, 4]$

By definition

$$\begin{aligned} m[3,4] &= \min_{3 \leq k < 4} (m[3,k] + m[k+1,4] + p_2 p_k p_4) \\ &= m[3,3] + m[4,4] + p_2 p_3 p_4 = 84. \end{aligned}$$

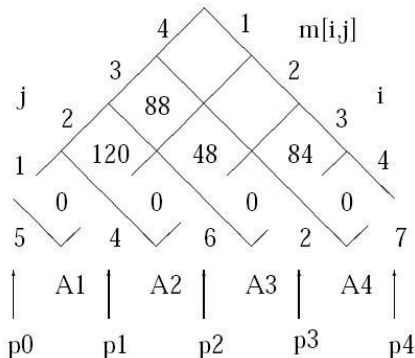


Example – Continued

Step 4: Computing $m[1,3]$

By definition

$$\begin{aligned}
 m[1,3] &= \min_{1 \leq k < 3} (m[1,k] + m[k+1,3] + p_0 p_k p_3) \\
 &= \min \begin{cases} m[1,1] + m[2,3] + p_0 p_1 p_3 \\ m[1,2] + m[3,3] + p_0 p_2 p_3 \end{cases} \\
 &= 88 .
 \end{aligned}$$

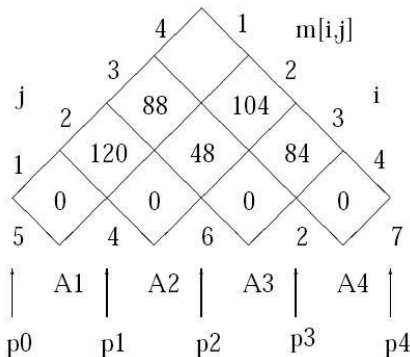


Example – Continued

Step 5: Computing $m[2, 4]$

By definition

$$\begin{aligned}
 m[2,4] &= \min_{2 \leq k < 4} (m[2,k] + m[k+1,4] + p_1 p_k p_4) \\
 &= \min \begin{cases} m[2,2] + m[3,4] + p_1 p_2 p_4 \\ m[2,3] + m[4,4] + p_1 p_3 p_4 \end{cases} \\
 &= 104 .
 \end{aligned}$$



Example – Continued

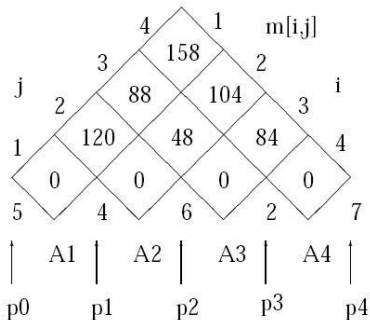
Step 6: Computing $m[1,4]$

By definition

$$m[1,4] = \min_{1 \leq k < 4} (m[1,k] + m[k+1,4] + p_0 p_k p_4)$$

$$= \min \begin{cases} m[1,1] + m[2,4] + p_0 p_1 p_4 \\ m[1,2] + m[3,4] + p_0 p_2 p_4 \\ m[1,3] + m[4,4] + p_0 p_3 p_4 \end{cases}$$

$$= 158$$



Constructing a Solution

- $m[i, j]$ only keeps costs but not actual multiplication sequence.
- To solve problem, need to reconstruct multiplication sequence that yields $m[1, n]$.
- Solution: similar to previous DP algorithm(s) keep an auxiliary array $s[*, *]$.
- $s[i, j] = k$ where k is the index that achieves minimum in

$$m[i, j] = \min_{i \leq k < j} (m[i, k] + m[k + 1, j] + p_{i-1}p_kp_j).$$

Developing a Dynamic Programming Algorithm

Step 4: Constructing optimal solution

Idea: Maintain an array $s[1..n, 1..n]$, where $s[i, j]$ denotes k for the optimal splitting in computing $A_{i..j} = A_{i..k}A_{k+1..j}$.

Developing a Dynamic Programming Algorithm

Step 4: Constructing optimal solution

Idea: Maintain an array $s[1..n, 1..n]$, where $s[i, j]$ denotes k for the optimal splitting in computing $A_{i..j} = A_{i..k}A_{k+1..j}$.

Question

How to Recover the Multiplication Sequence using $s[i, j]$?

Developing a Dynamic Programming Algorithm

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$$s[1, n] \quad (A_1 \cdots A_{s[1, n]}) (A_{s[1, n]+1} \cdots A_n)$$

Developing a Dynamic Programming Algorithm

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How to Recover the Multiplication Sequence using $s[i, j]$?

$$\begin{array}{ll} s[1, n] & (A_1 \cdots A_{s[1, n]}) (A_{s[1, n]+1} \cdots A_n) \\ s[1, s[1, n]] & (A_1 \cdots A_{s[1, s[1, n]]}) (A_{s[1, s[1, n]]+1} \cdots A_{s[1, n]}) \end{array}$$

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Question

How to Recover the Multiplication Sequence using $s[i, j]$?

$s[1, n]$	$(A_1 \cdots A_{s[1, n]}) (A_{s[1, n]+1} \cdots A_n)$
$s[1, s[1, n]]$	$(A_1 \cdots A_{s[1, s[1, n]]}) (A_{s[1, s[1, n]]+1} \cdots A_{s[1, n]})$
$s[s[1, n]+1, n]$	$(A_{s[1, n]+1} \cdots A_{s[s[1, n]+1, n]}) (A_{s[s[1, n]+1, n]+1} \cdots A_n)$

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$s[1, s[1, n]]$	$(A_1 \cdots A_{s[1, s[1, n]]}) (A_{s[1, s[1, n]]+1} \cdots A_{s[1, n]})$
$s[s[1, n]+1, n]$	$(A_{s[1, n]+1} \cdots A_{s[s[1, n]+1, n]}) (A_{s[s[1, n]+1, n]+1} \cdots A_n)$
\vdots	\vdots

Developing a Dynamic Programming Algorithm

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Question

How to Recover the Multiplication Sequence using $s[i, j]$?

$$\begin{array}{ll} s[1, n] & (A_1 \cdots A_{s[1, n]}) (A_{s[1, n]+1} \cdots A_n) \\ s[1, s[1, n]] & (A_1 \cdots A_{s[1, s[1, n]]}) (A_{s[1, s[1, n]]+1} \cdots A_{s[1, n]}) \\ s[s[1, n]+1, n] & (A_{s[1, n]+1} \cdots A_{s[s[1, n]+1, n]}) (A_{s[s[1, n]+1, n]+1} \cdots A_n) \\ \vdots & \vdots \end{array}$$

Apply **recursively** until multiplication sequence is completely determined.

Example 2:

$$A_1 \quad 30 \times 35 \quad = p_0 \times p_1$$

$$A_2 \quad 35 \times 15 \quad = p_1 \times p_2$$

$$A_3 \quad 15 \times 5 \quad = p_2 \times p_3$$

$$A_4 \quad 5 \times 10 \quad = p_3 \times p_4$$

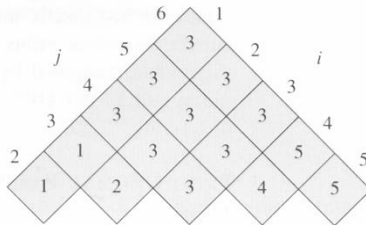
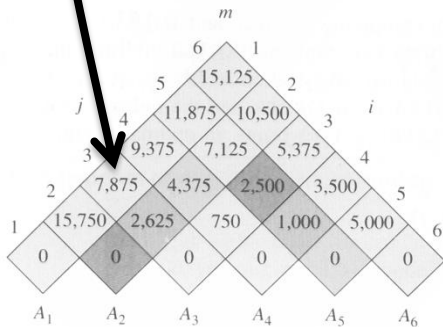
$$A_5 \quad 10 \times 20 \quad = p_4 \times p_5$$

$$A_6 \quad 20 \times 25 \quad = p_5 \times p_6$$

Matrix Size

A2 x A3 =	35 x 5	2,625
A1 (A2 x A3) =	30 X 5	5,250 + 2,625

the m and s table
computed by
MATRIX-CHAIN-
ORDER for $n=6$



$m[2,5]=$

$\min\{$

$m[2,2]+m[3,5]+p_1p_2p_5=0+2500+35\times15\times20=13000,$

$m[2,3]+m[4,5]+p_1p_3p_5=2625+1000+35\times5\times20=7125,$

$m[2,4]+m[5,5]+p_1p_4p_5=4375+0+35\times10\times20=11375$

$\}$

$=7125$

Constructing the optimal solution

PRINT-OPTIMAL-PARENS(s, i, j)

```
1  if  $i == j$ 
2      print " $A$ " $i$ 
3  else print "("
4      PRINT-OPTIMAL-PARENS( $s, i, s[i, j]$ )
5      PRINT-OPTIMAL-PARENS( $s, s[i, j] + 1, j$ )
6      print ")"
```

- **example:** $((A_1(A_2A_3))((A_4A_5)A_6))$

Constructing the optimal solution

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Example (Finding the Multiplication Sequence)

Consider $n = 6$. Assume array $s[1..6, 1..6]$ has been properly constructed.

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Consider $n = 6$. Assume array $s[1..6, 1..6]$ has been properly constructed. The multiplication sequence is recovered as follows.

$$s[1, 6] = 3 \quad (A_1 A_2 A_3)(A_4 A_5 A_6)$$

Example (Finding the Multiplication Sequence)

Consider $n = 6$. Assume array $s[1..6, 1..6]$ has been properly constructed. The multiplication sequence is recovered as follows.

$$\begin{aligned}s[1, 6] &= 3 && (A_1 A_2 A_3)(A_4 A_5 A_6) \\s[1, 3] &= 1\end{aligned}$$

Example (Finding the Multiplication Sequence)

Consider $n = 6$. Assume array $s[1..6, 1..6]$ has been properly constructed. The multiplication sequence is recovered as follows.

$$\begin{array}{ll} s[1,6] = 3 & (A_1 A_2 A_3)(A_4 A_5 A_6) \\ s[1,3] = 1 & (A_1(A_2 A_3)) \end{array}$$

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Consider $n = 6$. Assume array $s[1..6, 1..6]$ has been properly constructed. The multiplication sequence is recovered as follows.

$$\begin{array}{ll} s[1,6] = 3 & (A_1 A_2 A_3)(A_4 A_5 A_6) \\ s[1,3] = 1 & (A_1(A_2 A_3)) \\ s[4,6] = 5 & \end{array}$$

Example (Finding the Multiplication Sequence)

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Hence the final multiplication sequence is

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Hence the final multiplication sequence is

$$(A_1(A_2 A_3))((A_4 A_5)A_6).$$

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

for $i = 1$ **to** n **do** $m[i, i] =$

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

```
for  $i = 1$  to  $n$  do  $m[i, i] = 0$ ;  
;  
for  $l =$ 
```

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

```
for  $i = 1$  to  $n$  do  $m[i, i] = 0$ ;  
;  
for  $l = 2$  to
```

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

for $i = 1$ **to** n **do** $m[i, i] = 0$;

;

for $l = 2$ **to** n **do**

for $i = 1$ **to**

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

for $i = 1$ **to** n **do** $m[i, i] = 0$;

;

for $l = 2$ **to** n **do**

for $i = 1$ **to** $n - l + 1$ **do**

$j =$

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

```
for  $i = 1$  to  $n$  do  $m[i, i] = 0$ ;  
;  
for  $l = 2$  to  $n$  do  
    for  $i = 1$  to  $n - l + 1$  do  
         $j = i + l - 1$ ;  
         $m[i, j] =$ 
```

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

for $i = 1$ **to** n **do** $m[i, i] = 0$;

;

for $l = 2$ **to** n **do**

for $i = 1$ **to** $n - l + 1$ **do**

$j = i + l - 1$;

$m[i, j] = \infty$;

for $k =$

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

for $i = 1$ **to** n **do** $m[i, i] = 0$;

;

for $l = 2$ **to** n **do**

for $i = 1$ **to** $n - l + 1$ **do**

$j = i + l - 1$;

$m[i, j] = \infty$;

for $k = i$ **to**

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

```
for  $i = 1$  to  $n$  do  $m[i, i] = 0$ ;  
;  
for  $l = 2$  to  $n$  do  
    for  $i = 1$  to  $n - l + 1$  do  
         $j = i + l - 1$ ;  
         $m[i, j] = \infty$ ;  
        for  $k = i$  to  $j - 1$  do  
             $q =$ 
```

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

```
for  $i = 1$  to  $n$  do  $m[i, i] = 0$ ;  
;  
for  $l = 2$  to  $n$  do  
    for  $i = 1$  to  $n - l + 1$  do  
         $j = i + l - 1$ ;  
         $m[i, j] = \infty$ ;  
        for  $k = i$  to  $j - 1$  do  
             $q = m[i, k] +$ 
```

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

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$q = m[i, k] + m[k + 1, j] + p[i - 1] * p[k] * p[j]$;

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        end  
    end  
end  
end return
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```

(Optimum in

The Dynamic Programming Algorithm

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```

Complexity: The loops are nested three levels deep.

The Dynamic Programming Algorithm

Matrix-Chain(p, n): // l is length of sub-chain

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for  $i = 1$  to  $n$  do  $m[i, i] = 0$ ;  
;  
for  $l = 2$  to  $n$  do /  $l$  is the chain length  
    for  $i = 1$  to  $n - l + 1$  do  
         $j = i + l - 1$ ;  
         $m[i, j] = \infty$ ;  
        for  $k = i$  to  $j - 1$  do  
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The Dynamic Programming Algorithm

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    end  
end  
return  $m$  and  $s$ ; (Optimum in  $m[1, n]$ )
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Complexity: The loops are nested three levels deep. Each loop index takes on $\leq n$ values. Hence the **time complexity** is $O(n^3)$. **Space complexity** is $\Theta(n^2)$.

Introduction to Algorithms

Thomas H. Cormen

Chapter # 15