



Algorithms Theory

14 – Dynamic Programming (2) Matrix-chain multiplication

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Optimal substructure



Dynamic programming is typically applied to
optimization problems.

An optimal solution to the original problem contains
optimal solutions to smaller subproblems.



Matrix-chain multiplication

Given: sequence (chain) $\langle A_1, A_2, \dots, A_n \rangle$ of matrices

Goal: compute the product $A_1 \cdot A_2 \cdot \dots \cdot A_n$

Problem: Parenthesize the product in a way that **minimizes the number of scalar multiplications**.

Definition: A product of matrices is **fully parenthesized** if it is either a **single matrix** or the product of two fully parenthesized matrix products, **surrounded by parentheses**.

Examples of fully parenthesized matrix products of the chain $\langle A_1, A_2, \dots, A_n \rangle$



All possible fully parenthesized matrix products of the chain $\langle A_1, A_2, A_3, A_4 \rangle$ are:

$$(A_1(A_2(A_3A_4)))$$

$$(A_1((A_2A_3)A_4))$$

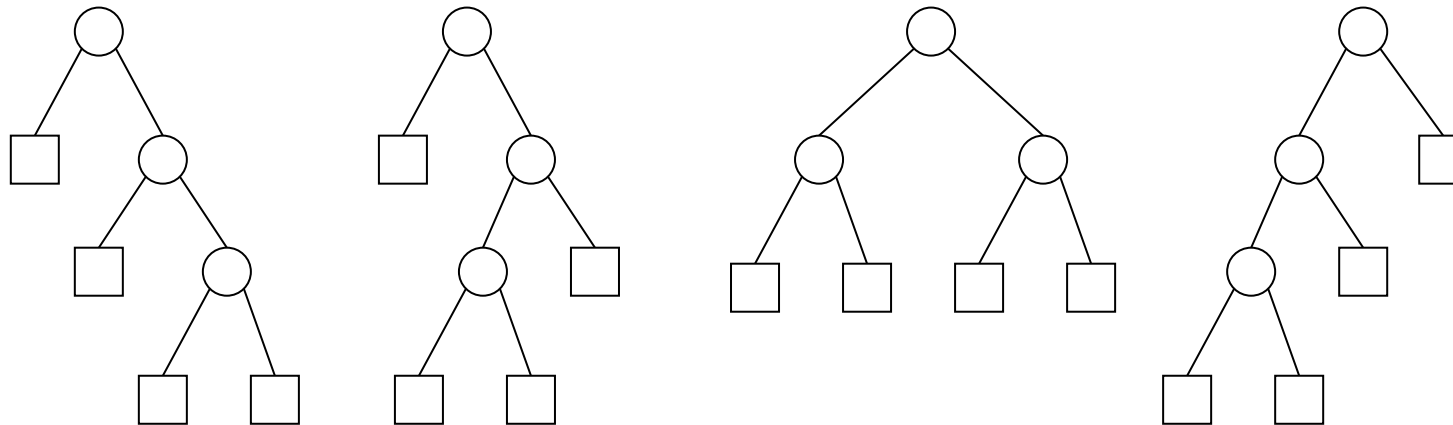
$$((A_1A_2)(A_3A_4))$$

$$((A_1(A_2A_3))A_4)$$

$$(((A_1A_2)A_3)A_4)$$

Number of different parenthesizations

Different parenthesizations correspond to different trees:



Number of different parenthesizations

Let $P(n)$ be the number of alternative parenthesizations of the product $A_1 \cdots A_k A_{k+1} \cdots A_n$.

$$P(1) = 1$$

$$P(n) = \sum_{k=1}^{n-1} P(k)P(n-k) \quad \text{for } n \geq 2$$

$$P(n+1) = \frac{1}{n+1} \binom{2n}{n} \approx \frac{4^n}{n\sqrt{\pi n}} + O\left(\frac{4^n}{\sqrt{n^5}}\right)$$

$$P(n+1) = C_n \quad n\text{-th Catalan number}$$

Remark: Determining the optimal parenthesization by exhaustive search is not reasonable.

Multiplying two matrices

$$A = (a_{ij})_{p \times q}, B = (b_{ij})_{q \times r}, A \cdot B = C = (c_{ij})_{p \times r},$$

$$c_{ij} = \sum_{k=1}^q a_{ik} b_{kj}.$$

Algorithm *Matrix-Mult*

Input: $(p \times q)$ matrix A , $(q \times r)$ matrix B

Output: $(p \times r)$ matrix $C = A \cdot B$

```
1 for  $i := 1$  to  $p$  do
2   for  $j := 1$  to  $r$  do
3      $C[i, j] := 0$ 
4     for  $k := 1$  to  $q$  do
5        $C[i, j] := C[i, j] + A[i, k] \cdot B[k, j]$ 
```

Number of multiplications and additions: $p \cdot q \cdot r$

Remark: Using this algorithm, multiplying two $(n \times n)$ matrices requires n^3 multiplications. This can also be done using $O(n^{2.376})$ multiplications.

Matrix-chain multiplication: Example

Computation of the product $A_1 A_2 A_3$, where

A_1 : (10 × 100) matrix

A_2 : (100 × 5) matrix

A_3 : (5 × 50) matrix

a) Parenthesization (($A_1 A_2$) A_3) requires

$A' = (A_1 A_2)$:

$A' A_3$:

Sum:

Matrix-chain multiplication: Example

A_1 : (10×100) matrix

A_2 : (100×5) matrix

A_3 : (5×50) matrix

a) Parenthesization $(A_1 (A_2 A_3))$ requires

$A'' = (A_2 A_3)$:

$A_1 A''$:

Sum:

Structure of an optimal parenthesization

$$(A_{i\dots j}) = ((A_{i\dots k}) (A_{k+1\dots j})) \quad i \leq k < j$$

Any optimal solution to the matrix-chain multiplication problem contains optimal solutions to subproblems.

Determining an optimal solution recursively:

Let $m[i,j]$ be the **minimum number of operations** needed to compute the product $A_{i\dots j}$:

$$m[i,j] = 0, \quad \text{if } i = j$$

$$m[i,j] = \min_{i \leq k < j} \{m[i,k] + m[k+1,j] + p_{i-1}p_kp_j\}, \quad \text{otherwise}$$

$s[i,j]$ = **optimal splitting value k** , i.e. the optimal parenthesization of $(A_{i\dots j})$ splits the product between A_k and A_{k+1}

Recursive matrix-chain multiplication

Algorithm *rec-mat-chain*(p, i, j)

Input: sequence $p = \langle p_0, p_1, \dots, p_n \rangle$,

where $(p_{i-1} \times p_i)$ is the dimension of matrix A_i

Invariant: *rec-mat-chain*(p, i, j) returns $m[i, j]$

1 **if** $i = j$ **then return** 0

2 $m[i, j] := \infty$

3 **for** $k := i$ **to** $j - 1$ **do**

4 $m[i, j] := \min(m[i, j], p_{i-1} p_k p_j +$
 rec-mat-chain(p, i, k) +
 rec-mat-chain($p, k+1, j$))

5 **return** $m[i, j]$

Initial call: *rec-mat-chain*($p, 1, n$)

Recursive matrix-chain multiplication: Running time



Let $T(n)$ be the time taken by $\text{rec-mat-chain}(p, 1, n)$.

$$\begin{aligned}T(1) &\geq 1 \\T(n) &\geq 1 + \sum_{k=1}^{n-1} (T(k) + T(n-k) + 1) \\&\geq n + 2 \sum_{i=1}^{n-1} T(i) \\&\Rightarrow T(n) \geq 3^{n-1} \quad (\text{induction})\end{aligned}$$

Exponential running time!

Matrix-chain multiplication using dynamic programming



Algorithm *dyn-mat-chain*

Input: sequence $p = \langle p_0, p_1, \dots, p_n \rangle$, $(p_{i-1} \times p_i)$ the dimension of matrix A_i

Output: $m[1, n]$

```
1   $n := \text{length}(p) - 1$ 
2  for  $i := 1$  to  $n$  do  $m[i, i] := 0$ 
3  for  $l := 2$  to  $n$  do                                /*  $l = \text{length of the subproblem}$  */
4  for  $i := 1$  to  $n - l + 1$  do                          /*  $i$  is the left index */
5       $j := i + l - 1$                                     /*  $j$  is the right index */
6       $m[i, j] := \infty$ 
7      for  $k := i$  to  $j - 1$  do
8           $m[i, j] := \min( m[i, j], p_{i-1} p_k p_j + m[i, k] + m[k + 1, j] )$ 
9  return  $m[1, n]$ 
```

Example



A_1 (30 × 35)

A_4 (5 × 10)

A_2 (35 × 15)

A_5 (10 × 20)

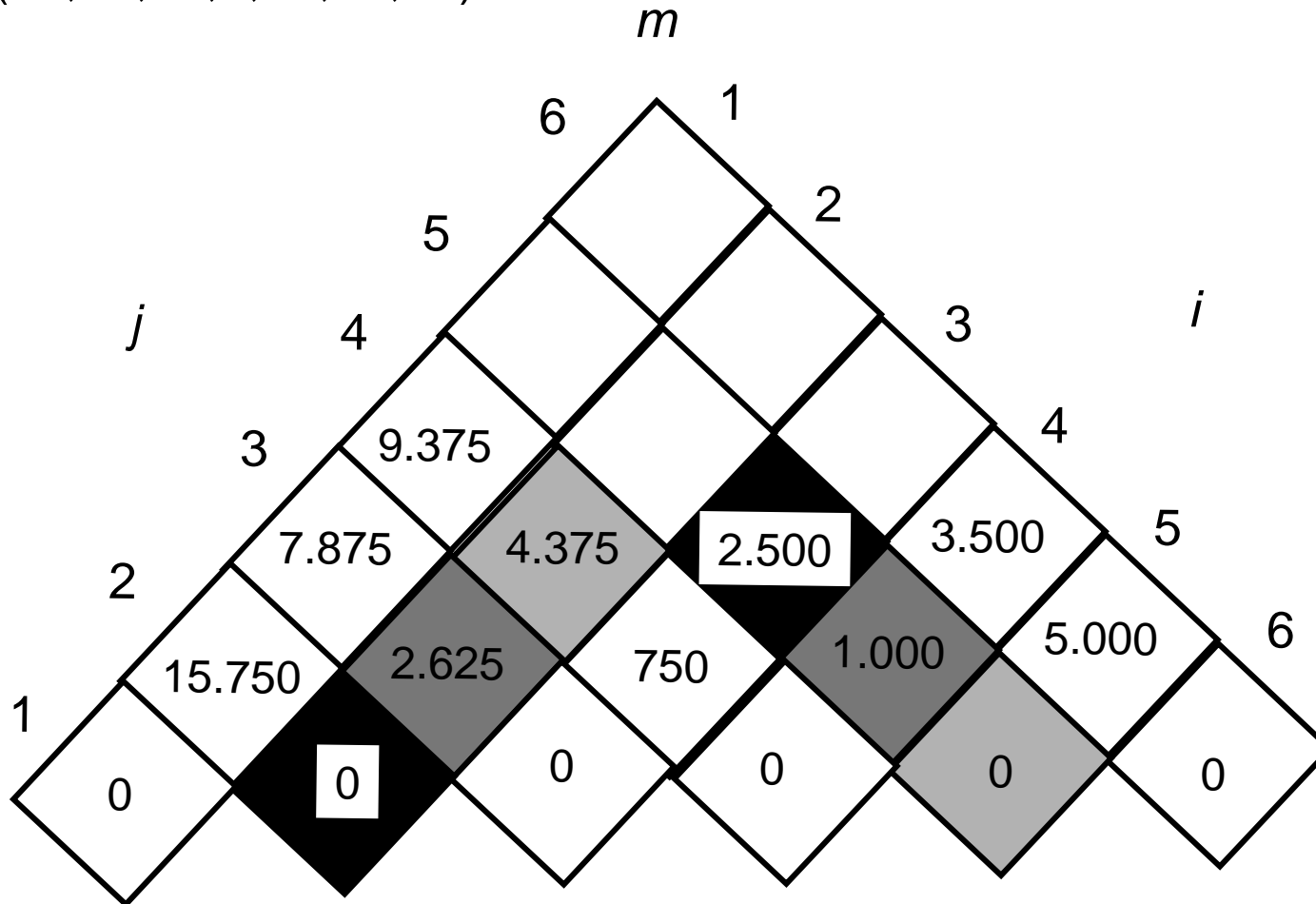
A_3 (15 × 5)

A_6 (20 × 25)

$p = (30, 35, 15, 5, 10, 20, 25)$

Example

$$p = (30, 35, 15, 5, 10, 20, 25)$$



Example



$$\begin{aligned} m[2,5] &= \min_{2 \leq k < 5} (m[2,k] + m[k+1,5] + p_1 p_k p_5) \\ &= \min \begin{cases} m[2,2] + m[3,5] + p_1 p_2 p_5 \\ m[2,3] + m[4,5] + p_1 p_3 p_5 \\ m[2,4] + m[5,5] + p_1 p_4 p_5 \end{cases} \\ &= \min \begin{cases} 0 + 2500 + 35 \cdot 15 \cdot 20 = 13000 \\ 2625 + 1000 + 35 \cdot 5 \cdot 20 = 7125 \\ 4375 + 0 + 35 \cdot 10 \cdot 20 = 11375 \end{cases} \\ &= 7125 \end{aligned}$$

Matrix-chain multiplication and optimal splitting values using dynamic programming



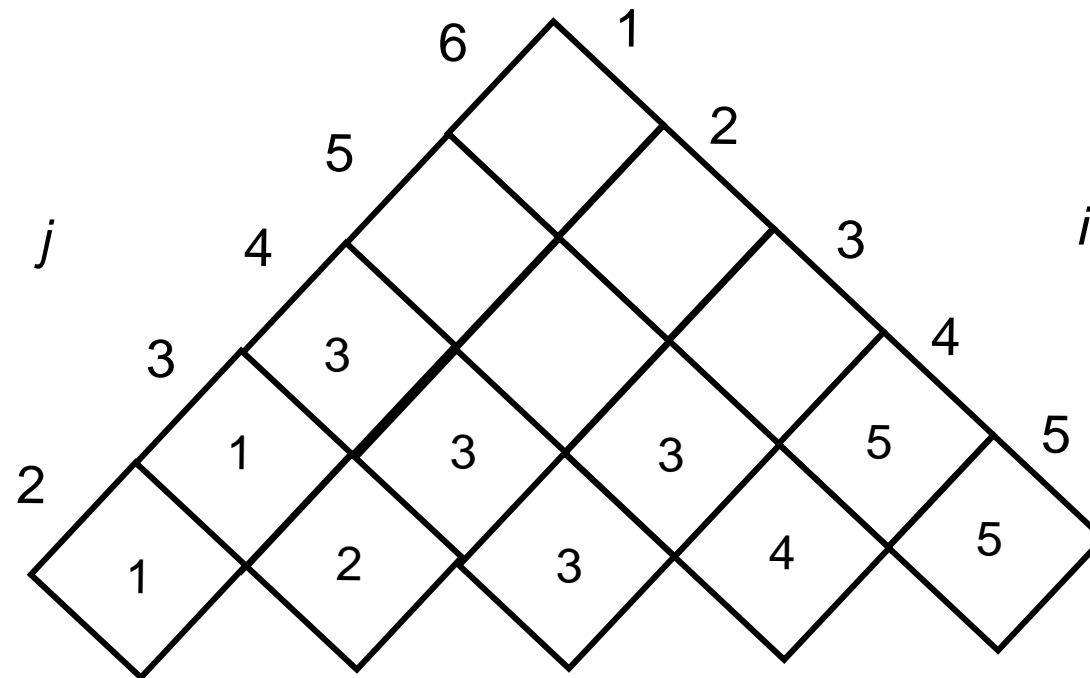
Algorithm *dyn-mat-chain*(p)

Input: sequence $p = \langle p_0, p_1, \dots, p_n \rangle$, $(p_{i-1} \times p_i)$ the dimension of matrix A_i

Output: $m[1, n]$ and a matrix $s[i, j]$ containing the optimal splitting values

```
1  $n := \text{length}(p) - 1$ 
2 for  $i := 1$  to  $n$  do  $m[i, i] := 0$ 
3 for  $l := 2$  to  $n$  do
4   for  $i := 1$  to  $n - l + 1$  do
5      $j := i + l - 1$ 
6      $m[i, j] := \infty$ 
7     for  $k := i$  to  $j - 1$  do
8        $q := m[i, j]$ 
9        $m[i, j] := \min( m[i, j], p_{i-1} p_k p_j + m[i, k] + m[k + 1, j] )$ 
10      if  $m[i, j] < q$  then  $s[i, j] := k$ 
11 return  $(m[1, n], s)$ 
```

Example of splitting values



Computation of an optimal parenthesization



Algorithm *Opt-Parens*

Input: chain A of matrices, matrix s containing the optimal splitting values, two indices i and j

Output: an optimal parenthesization of $A_{i..j}$

```
1  if  $i < j$ 
2    then  $X := \text{Opt-Parens}(A, s, i, s[i, j])$ 
3          $Y := \text{Opt-Parens}(A, s, s[i, j] + 1, j)$ 
4         return  $(X \cdot Y)$ 
5  else return  $A_i$ 
```

Initial call: $\text{Opt-Parens}(A, s, 1, n)$

Matrix-chain multiplication using dynamic programming (top-down approach)



„*Memoization*“ for increasing the efficiency of a recursive solution:

Only the *first time* a subproblem is encountered, its **solution is computed** and then stored in a table. Each subsequent time that the subproblem is encountered, the value stored in the table is simply looked up and returned (without repeated computation!).

Memoized matrix-chain multiplication („notepad method“)



Algorithm *mem-mat-chain*(p, i, j)

Invariant: *mem-mat-chain*(p, i, j) returns $m[i, j]$;
the value is correct if $m[i, j] < \infty$

```
1 if  $i = j$  then return 0
2 if  $m[i, j] < \infty$  then return  $m[i, j]$ 
3 for  $k := i$  to  $j - 1$  do
4      $m[i, j] := \min( m[i, j], p_{i-1} p_k p_j +$   
                    mem-mat-chain( $p, i, k$ ) +  
                    mem-mat-chain( $p, k + 1, j$ ) )
5 return  $m[i, j]$ 
```

Memoized matrix-chain multiplication

Call:

```
1  $n := \text{length}(p) - 1$ 
2 for  $i := 1$  to  $n$  do
3   for  $j := 1$  to  $n$  do
4      $m[i, j] := \infty$ 
5 mem-mat-ket( $p, 1, n$ )
```

The computation of all entries $m[i, j]$ using *mem-mat-chain* takes $O(n^3)$ time.

$O(n^2)$ entries

each entry $m[i, j]$ is computed once

each entry $m[i, j]$ is looked up during the computation of $m[i', j']$ if
 $i' = i$ and $j' > j$ or $j' = j$ and $i' < i$

→ $m[i, j]$ is looked up during the computation of at most $2n$ entries

Remarks about matrix-chain multiplication



1. There is an algorithm that determines an optimal parenthesization in time $O(n \log n)$.
2. There is a linear time algorithm that determines a parenthesization using most $1.155 \cdot M_{opt}$ multiplications.