

07. Dynamic Programming for Matrix Chain Multiplication

CPSC 535

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Big Idea: 2D Table

- ▶ *Recall:* dynamic programming
 - ▶ problem has recursive structure
 - ▶ overlapping subproblems
 - ▶ use table to store solutions, avoid duplicated effort
 - ▶ top-down or bottom-up
- ▶ so far: **1D table** – has one index
- ▶ now: **2D table** – has *two* indices

Recap: Dynamic Programming Design Process

1. Identify the problem's **solution** and **value**, and note which is our **goal**.
2. Derive a **recurrence** for an optimal value.
3. Design a divide-and-conquer algorithm that computes an **optimal value**.
4. Design a dynamic programming algorithm that computes an **optimal value**.
 - 4.1 **top-down** alternative: add table base case (**memoization**)
 - 4.2 **bottom-up** alternative: rewrite to use bottom-up loops instead of recursion
5. (if goal is a solution algo.) Design a dynamic programming algorithm that computes an **optimal solution**.

Rod Cutting Step 5

5. (if goal is a solution algo.) Design a dynamic programming algorithm that computes an **optimal solution**.

rod cutting value problem

input: an array of non-negative prices $P = \langle p_1, \dots, p_n \rangle$

output: the maximum total price that can be achieved by cutting an n -inch rod into pieces

rod cutting problem

input: an array of non-negative prices $P = \langle p_1, \dots, p_n \rangle$

output: the list of cut-lengths of maximum total price for an n -inch rod

Recap: Rod Cutting Step 4.b

```
1: function CUT-ROD-BU( $P[1..n]$ )
2:   Create array  $R[0..n]$ 
3:    $R[0] = 0$ 
4:   for  $j$  from 1 to  $n$  do
5:      $q = -\infty$ 
6:     for  $i$  from 1 to  $j$  do
7:        $q = \max(q, P[i] + R[j - i])$ 
8:     end for
9:      $R[j] = q$ 
10:  end for
11:  return  $R[n]$ 
12: end function
```

Moving from Values to Solutions

- ▶ **value** version of rod cutting: output is a number (total price)
- ▶ **solution** version: output is a list of cuts
- ▶ Example: for input $n = 11$, output might be $\langle 4, 4, 2, 1 \rangle$
- ▶ Naïve approach: $R[i]$ stores a list of cuts, instead of just a number

Rod Cutting Step 5 – First Draft

```
1: function CUT-ROD-SOLUTION( $P[1..n]$ )
2:   Create array  $R[0..n]$ 
3:    $R[0] = \langle \rangle$  ▷ empty sequence
4:   for  $j$  from 1 to  $n$  do
5:      $q = \langle \rangle$ 
6:     for  $i$  from 1 to  $j$  do
7:        $\text{cut-}i = R[j - i] \cup \langle j \rangle$  ▷ copy of  $R[j - i]$  with  $j$  appended
8:       if TOTAL-PRICE( $P$ ,  $\text{cut-}i$ ) > TOTAL-PRICE( $P$ ,  $q$ ) then
9:          $q = \text{cut-}i$ 
10:      end if
11:    end for
12:     $R[j] = q$ 
13:  end for
14:  return  $R[n]$ 
15: end function
```

Rod Cutting Step 5 – First Draft

```
1: function TOTAL-PRICE( $P[1..n]$ , cuts)
2:    $x = 0$ 
3:   for  $j$  in cuts do
4:      $x = x + P[j]$ 
5:   end for
6:   return  $x$ 
7: end function
```


Analysis

- ▶ worst-case length of an $R[j]$ is $\Theta(n)$
 - ▶ (all 1-cuts)
- ▶ so TOTAL-PRICE takes $\Theta(n)$ time
- ▶ creating each cut- i takes $\Theta(n)$ time
- ▶ CUT-ROD-SOLUTION takes $\Theta(n^3)$ time
- ▶ **space** is an issue: CUT-ROD-SOLUTION takes $\Theta(n^2)$ space

Backtracking

- ▶ algorithm computes optimal value, and **logs (records) how it made each decision**
- ▶ after all optimal values have been computed, follow a “trail” to create solution object
- ▶ trail ends at the optimal solution
- ▶ each log entry says how to go one step backwards
- ▶ follow them until we get to the start (a base case)
- ▶ traverses solution in backwards order; reverse it if order matters
- ▶ backtracking is usually only $\Theta(n)$ time, and $\Theta(n)$ space overhead

Rod Cutting Step 5

5. (if goal is a solution algo.) Design a dynamic programming algorithm that computes an **optimal solution**.
- ▶ bottom-up algo. makes optimal choices with

$$q = \max(q, P[i] + R[j - i])$$

step

- ▶ i.e. it chooses how many inches to cut right now
- ▶ **log** these choices in another array
- ▶ recall $R[j]$ = maximum total price starting from j inches
- ▶ define $S[j]$ = size of the first optimal cut starting from j inches
- ▶ need to update pseudocode to
 - ▶ create S
 - ▶ update S inside the loops
 - ▶ at the end, backtrack S to compute a list of lengths

Rod Cutting Step 5 – Pseudocode

```
1: function CUT-ROD-SOLUTION( $P[1..n]$ )
2:   Create arrays  $R[0..n]$  and  $S[0..n]$ 
3:    $R[0] = 0$ 
4:   for  $j$  from 1 to  $n$  do
5:      $q = -\infty$ 
6:     for  $i$  from 1 to  $j$  do
7:       if  $q < (P[i] + R[j - i])$  then
8:          $q = P[i] + R[j - i]$ 
9:          $S[j] = i$ 
10:      end if
11:    end for
12:     $R[j] = q$ 
13:  end for
14:  return CUT-ROD-BACKTRACK( $S, n$ )
15: end function
```

Rod Cutting Step 5 – Pseudocode

```
1: function CUT-ROD-BACKTRACK( $S[0..n]$ ,  $n$ )
2:   cuts =  $\langle \rangle$ 
3:    $j = n$ 
4:   while  $j > 0$  do
5:     cuts.append( $S[j]$ )
6:      $j = j - S[j]$ 
7:   end while
8:   cuts.reverse()
9:   return cuts
10: end function
```

▷ empty sequence

▷ remaining rod

▷ put in forward order

Analysis

- ▶ CUT-ROD-SOLUTION solves the *rod cutting problem*
 - ▶ it returns a list of cut-lengths, not a price
- ▶ analysis is actually straightforward
- ▶ time efficiency:
 - ▶ nested **for** loops: $\Theta(n^2)$
 - ▶ backtracking: **while** loop iterates at most n times $\Rightarrow \Theta(n)$ time
 - ▶ reverse soln: $\Theta(n)$
 - ▶ total $\Theta(n^2 + n + n) = \Theta(n^2)$ time
- ▶ space efficiency: R and S take $\Theta(n + n) = \Theta(n)$ space
- ▶ (same as the step-4 algorithms)

Matrix Multiplication

for matrices A_1, A_2 :

$$A_1 A_2$$

Recall:

$$\begin{bmatrix} 5 & 12 & 5 \\ 16 & 9 & 4 \end{bmatrix} \times \begin{bmatrix} 19 & 2 \\ 9 & 5 \\ 8 & 11 \end{bmatrix} = \begin{bmatrix} 5 \times 19 + 12 \times 9 + 5 \times 8 & 125 \\ 417 & 121 \end{bmatrix}$$

Matrix Multiplication Algorithms

Recall:

- ▶ Naïve algorithm: three nested loops, $O(n^3)$
- ▶ Strassen's algorithm: divide-and-conquer, $\approx O(n^{2.8074})$
- ▶ Those analyses assumed A_1, A_2 are both square $n \times n$ matrices
- ▶ Now: matrix sizes may differ
- ▶ **Compatible:** A_1 and A_2 are compatible when $A_1.columns = A_2.rows$

Naïve Matrix Multiplication Algorithm

```
1: function MATRIX-MULTIPLY(A, B)
2:   C = new A.rows × B.columns matrix
3:   for i from 1 to A.rows do
4:     for j from 1 to B.columns do
5:       cij = 0
6:       for k from 1 to A.columns do
7:         cij = cij + aik · bkj
8:       end for
9:     end for
10:  end for
11:  return C
12: end function
```

Analysis: $\Theta(A.rows \times A.columns \times B.columns)$

Matrix Chain Multiplication

Given n compatible matrices A_1, A_2, \dots, A_n , compute

$$A_1 A_2 \dots A_n$$

- ▶ Recall: matrix multiplication is **associative**
- ▶ May parenthesize $A_1 A_2 \dots A_n$ in any order
- ▶ Q: which order is most efficient?

Equivalent Parenthesizations

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

Total runtime depends on the dimensions of $A_1 \dots A_4$.

Example: Different Runtimes

Given three matrices A_1, A_2, A_3 with dimensions

matrix	rows	columns
A_1	10	100
A_2	100	5
A_3	5	50

- ▶ $((A_1 A_2) A_3)$ costs $10 \cdot 100 \cdot 5 + 10 \cdot 5 \cdot 50 = 5,000 + 2,500 = 7,500$ multiply operations
- ▶ $(A_1 (A_2 A_3))$ costs $100 \cdot 5 \cdot 50 + 10 \cdot 100 \cdot 50 = 25,000 + 50,000 = 75,000$ mult. operations
- ▶ first is order of magnitude faster

Matrix Chain Multiplication Problem

matrix chain multiplication problem

input: a sequence $\langle A_1, A_2, \dots, A_n \rangle$ of $n > 0$ compatible matrices, and sequence $p = \langle p_0, p_1, \dots, p_n \rangle$ of integers, where matrix A_i has p_{i-1} rows and p_i columns

output: a parenthesization of $A_1 A_2 \dots A_n$ that minimizes scalar multiplications

matrix chain multiplication value problem

input: a sequence $\langle A_1, A_2, \dots, A_n \rangle$ of $n > 0$ compatible matrices, and sequence $p = \langle p_0, p_1, \dots, p_n \rangle$ of integers, where matrix A_i has p_{i-1} rows and p_i columns

output: the minimum number of scalar multiplies necessary to multiply $A_1 A_2 \dots A_n$

Design Process

1. Identify the problem's **solution** and **value**, and note which is our **goal**.
2. Derive a **recurrence** for an optimal value.
3. Design a divide-and-conquer algorithm that computes an **optimal value**.
4. Design a dynamic programming algorithm that computes an **optimal value**.
 - 4.1 **top-down** alternative: add table base case (**memoization**)
 - 4.2 **bottom-up** alternative: rewrite to use bottom-up loops instead of recursion
5. (if goal is a solution algo.) Design a dynamic programming algorithm that computes an **optimal solution**.

Matrix Chain Multiplication Step 1

1. Identify the problem's **solution** and **value**, and note which is our **goal**.

matrix chain multiplication value problem

input: a sequence $\langle A_1, A_2, \dots, A_n \rangle$ of $n > 0$ compatible matrices, and sequence $p = \langle p_0, p_1, \dots, p_n \rangle$ of integers, where matrix A_i has p_{i-1} rows and p_i columns

output: the minimum number of scalar multiplies necessary to multiply $A_1 A_2 \dots A_n$

- ▶ **solution:** parenthesized expression e.g. $(A_1(A_2A_3))(A_4A_5)$
- ▶ **value:** number of multiplications e.g. 75,000
- ▶ goal: **value**

Matrix Chain Multiplication Step 2

2. Derive a **recurrence** for an optimal value.

- ▶ define $r_{i,j}$ = minimum number of multiplies for $A_i A_{i+1} \dots A_j$
- ▶ (note: **two** indices)
- ▶ solution to whole problem is $r_{1,n}$
- ▶ base case: A_i by itself; so when $i = j$, $r_{i,j} = 0$
- ▶ general case:
 - ▶ **think** divide-and-conquer; define $r_{i,j}$ in terms of $r_{<i,<j}$
 - ▶ make the problem **one piece** smaller
 - ▶ given $A_i A_{i+1} \dots A_j$, split w/ parenthesis at index k :

$$A_i A_{i+1} \dots A_j = (A_i A_{i+1} \dots A_k) (A_{k+1} A_{k+2} \dots A_j)$$

- ▶ try every option and keep the optimal one

$$r_{i,j} = \min_{i \leq k \leq j} r_{i,k} + r_{k+1,j} + p_{i-1} p_k p_j$$

Matrix Chain Multiplication Step 3

3. Design a divide-and-conquer algorithm that computes an **optimal value**.

```
1: function MATRIX-CHAIN-VALUE-DC( $p[0..n]$ )
2:   return MC-DC( $p, 0, n$ )
3: end function
4: function MC-DC( $p[0..n], i, j$ )
5:   if  $i == j$  then
6:     return 0
7:   end if
8:    $q = \infty$ 
9:   for  $k$  from  $i$  to  $j - 1$  do
10:     $q = \min(q, \text{MC-DC}(p, i, k) + \text{MC-DC}(p, k + 1, j) + p[i - 1] \times p[k] \times p[j])$ 
11:  end for
12:  return  $q$ 
13: end function
```

Sidebar: Analysis of MATRIX-CHAIN-VALUE-DC

- ▶ MC-DC-REC calls itself $O(n)$ times in general case
- ▶ like CUT-ROD-DC
- ▶ exponential time
- ▶ again, dynamic programming will circumvent all this recursion

Matrix Chain Multiplication Step 4.a

4. Design a dynamic programming algorithm that computes an **optimal value**.

4.1 **top-down** alternative: add table base case (**memoization**)

- ▶ Recall **memoization**: use a hash dictionary to make a “memo” of pre-calculated solutions
- ▶ create hash table T
- ▶ use pair (i, j) as key in table T , storing $r_{i,j}$

Matrix Chain Multiplication Step 4.a

```
1: function MATRIX-CHAIN-VALUE-MEMOIZED( $p[0..n]$ )
2:    $T = \text{HashTable}()$ 
3:   return MC-M( $T, p, 1, n$ )
4: end function
5: function MC-M( $T, p[0..n], i, j$ )
6:   if  $T.\text{contains}((i, j))$  then
7:     return  $T.\text{get}((i, j))$ 
8:   end if
9:   if  $i == j$  then
10:     $q = 0$ 
11:   else
12:     $q = \infty$ 
13:    for  $k$  from  $i$  to  $j - 1$  do
14:       $q = \min(q, \text{MC-M}(p, i, k) + \text{MC-M}(p, k + 1, j) + p[i - 1] \times p[k] \times p[j])$ 
15:    end for
16:   end if
17:    $T.\text{set}((i, j), q)$ 
18:   return  $q$ 
19: end function
```

Memoized Algorithm Analysis

- ▶ T contains $\Theta(n^2)$ pairs (i, j)
- ▶ each entry is inserted exactly once
- ▶ in the general case, MC-M takes $\Theta(n)$ expected time
- ▶ \Rightarrow MATRIX-CHAIN-VALUE-MEMOIZED takes $\Theta(n^3)$ expected time

Matrix Chain Multiplication Step 4.b

4. Design a dynamic programming algorithm that computes an **optimal value**.
 - 4.1 **top-down** alternative: add table base case (**memoization**)
 - 4.2 **bottom-up** alternative: rewrite to use bottom-up loops instead of recursion
- ▶ create 2D array m where $m[i][j] = r_{i,j}$
 - ▶ **bottom-up**: write an explicit **for** loop that computes and stores every general case
 - ▶ need to order loops so we never use an uninitialized element
 - ▶ \therefore initialize chain length 1(base case), $2, \dots, n$

Matrix Chain Multiplication Step 4.b

```
1: function MATRIX-CHAIN-BU( $p[0..n]$ )
2:   Create array  $m[1..n][1..n]$ 
3:   for  $i$  from 1 to  $n$  do
4:      $m[i][i] = 0$ 
5:   end for
6:   for  $\ell$  from 2 to  $n$  do
7:     for  $i$  from 1 to  $(n - \ell + 1)$  do
8:        $j = i + \ell - 1$ 
9:        $q = \infty$ 
10:      for  $k$  from  $i$  to  $j - 1$  do
11:         $q = \min(q, m[i][k] + m[k + 1][j] + p[i - 1] \times p[k] \times p[j])$ 
12:      end for
13:       $m[i][j] = q$ 
14:    end for
15:  end for
16:  return  $m[1][n]$ 
17: end function
```

▷ base case, length=1

▷ ℓ = general-case length

Matrix Chain Multiplication Analysis

- ▶ MATRIX-CHAIN-BU is clearly $\Theta(n^3)$ time
- ▶ top-down memoized algorithm: $\Theta(n^3)$ expected time
- ▶ bottom-up algorithm: $\Theta(n^3)$ time with faster constant factors

Matrix Chain Multiplication Step 5

5. (if goal is a solution algo.) Design a dynamic programming algorithm that computes an **optimal solution**.

matrix chain multiplication value problem

input: a sequence $\langle A_1, A_2, \dots, A_n \rangle$ of $n > 0$ compatible matrices, and sequence $p = \langle p_0, p_1, \dots, p_n \rangle$ of integers, where matrix A_i has p_{i-1} rows and p_i columns

output: the minimum number of scalar multiplies necessary to multiply $A_1 A_2 \dots A_n$

matrix chain multiplication problem

input: (same)

output: a parenthesization of $A_1 A_2 \dots A_n$ that minimizes scalar multiplications

Matrix Chain Multiplication Step 5

5. (if goal is a solution algo.) Design a dynamic programming algorithm that computes an **optimal solution**.

- ▶ **idea:** for each (i, j) , record which k defines the minimum $m[i][j]$
- ▶ happens inside the inner-most k loop
- ▶ define

$$s[i][j] = \text{the index } k \text{ that minimizes } r_{i,k} + r_{k+1,j} + p_{i-1}p_kp_j$$

- ▶ rewrite $\min(q, \dots)$ statement as an **if** so we can update $s[i][j]$

Matrix Chain Multiplication Step 5

```

1: function MATRIX-CHAIN-SOLUTION( $p[0..n]$ )
2:   Create arrays  $m[1..n][1..n]$  and  $s[1..n][1..n]$ 
3:   for  $i$  from 1 to  $n$  do
4:      $m[i][i] = 0$ 
5:   end for
6:   for  $\ell$  from 2 to  $n$  do
7:     for  $i$  from 1 to  $(n - \ell + 1)$  do
8:        $j = i + \ell - 1$ 
9:        $q = \infty$ 
10:      for  $k$  from  $i$  to  $j - 1$  do
11:         $q' = m[i][k] + m[k + 1][j] + p[i - 1] \times p[k] \times p[j]$ 
12:        if  $q' < q$  then
13:           $q = q'$ 
14:           $s[i][j] = k$ 
15:        end if
16:      end for
17:       $m[i][j] = q$ 
18:    end for
19:  end for
20:  return MC-BTRACK( $s, 1, n$ )
21: end function

```

▷ base case, length=1

▷ ℓ = general-case length

Matrix Chain Multiplication Step 5

```
1: function MC-PARENS( $s[1..n][1..n]$ ,  $i, j$ )
2:   if  $i == j$  then
3:     return " $A_i$ "
4:   end if
5:    $k = s[i][j]$ 
6:   return "(" + MC-PARENS( $s, i, k$ ) + ")" + MC-PARENS( $s, k, j$ ) + ")"
7: end function
```

▷ single matrix