

# DYNAMIC PROGRAMMING

- Obynamic Programming is a general algorithm design technique for solving problems defined by or formulated as recurrences with overlapping subinstances.
- •Invented by American mathematician Richard Bellman in the 1950s to solve optimization problems.
- o "Programming" here means "planning".



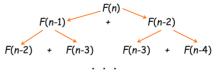
# DYNAMIC PROGRAMMING

- oMain idea:
  - set up a recurrence relating a solution to a larger instance to solutions of some smaller instances.
  - solve smaller instances once and record solutions in a table.
  - extract solution to the initial instance from that table.
- Different from divide-and-conquer which partitions the problem into independent sub-problems and solves them recursively.



# DYNAMIC PROGRAMMING

- Recall definition of Fibonacci numbers:
  - F(n) = F(n-1) + F(n-2)
  - F(0) = 0
  - F(1) = 1
- Computing the n<sup>th</sup> Fibonacci number recursively (top-down):



# DYNAMIC PROGRAMMING

- Dynamic programming applications:
  - Computing a binomial coefficient.
  - · Longest common subsequence.
  - Warshall's algorithm for transitive closure.
  - Floyd's algorithm for all-pairs shortest paths.
  - Constructing an optimal binary search tree.
  - Some instances of difficult discrete optimization problems:
    - o traveling salesman problem.
    - o knapsack problem.



## MATRIX CHAIN MULTIPLICATION

O Given an  $l \times m$  matrix A and an  $m \times q$  matrix B, the product

$$(l \times q)$$
  $(l \times m)$   $(m \times q)$ 

$$C = A \times B$$

is an  $l \times q$  matrix, where

$$C[i, j] = \sum_{k=1}^{m} A[i, k] \times B[k, j]$$

and the number of multiplications used to compute  ${\it C}$  is

$$l \times m \times q$$

#### MATRIX CHAIN MULTIPLICATION

• Assume *n* matrices are to be multiplied together:

$$(r_1 \times r_2)$$
  $(r_2 \times r_3)$   $(r_3 \times r_4)$  ...  $(r_{n-1} \times r_n)$   $(r_n \times r_{n+1})$ 

$$M_1 \quad M_2 \quad M_3 \quad ... \quad M_{n-1} \quad M_n$$

where each matrix  $M_i$  has  $r_i$  rows and  $r_{i+1}$  columns for  $1 \le i \le n$ .

# MATRIX CHAIN MULTIPLICATION

- The product can be computed in many different **orders**!
- Example 1: Let's compute the product of four matrices.

$$A \times B \times C \times D$$

there are 5 different ways:

- 1.  $(((A \times B) \times C) \times D)$
- 4.  $((A\times(B\times C))\times D)$
- 2. (A×((B×C)×D))
  3. ((A×B)×(C×D))
- 5.  $(A\times(B\times(C\times D)))$



# MATRIX CHAIN MULTIPLICATION

OWay 1: 44 multiplications

 $\begin{array}{lll} \text{(A\times B)} & \text{((A\times B)\times C)} & \text{(((A\times B)\times C)\times D)} \\ \text{4\times2\times3=24} & \text{4\times3\times1=12} & \text{4\times1\times2=8} \\ \end{array}$ 

OWay 5: 34 multiplications

(CxD) (Bx(CxD)) (Ax(Bx(CxD)))3x1x2=6 2x3x2=12 4x2x2=16

#### MATRIX CHAIN MULTIPLICATION

• Example 2: Given the matrix chain  $A_p$ ,  $A_2$ ,  $A_3$ ,  $A_4$  and matrix sizes:

$$size(A_1) = \frac{30 \times 1}{1}$$
,  $size(A_2) = \frac{1 \times 40}{1}$ ,  
 $size(A_3) = \frac{40 \times 10}{1}$ ,  $size(A_4) = \frac{10 \times 25}{1}$ .

Order of multiplications	Number of scalar multiplications
$(\mathbf{A}_1 \times (\mathbf{A}_2 \times (\mathbf{A}_3 \times \mathbf{A}_4)))$	40*10*25+1*40*25+30*1*25 =1,750
$(A_1 \times ((A_2 \times A_3) \times A_4))$	1*40*10+1*10*25+30*1*25 = 1,400
$((\mathbf{A}_1 \times \mathbf{A}_2) \times (\mathbf{A}_3 \times \mathbf{A}_4))$	30*1*40+40*10*25+30*40*25 = 41,200
$((\mathbf{A}_1 \times (\mathbf{A}_2 \times \mathbf{A}_3 )) \times \mathbf{A}_4)$	1*40*10+30*1*10+30*10*25 = 8,200
$(((\mathbf{A}_1 \times \mathbf{A}_2) \times \mathbf{A}_3) \times \mathbf{A}_4)$	30*1*40+30*40*10+30*10*25 = 20,700

## MATRIX CHAIN MULTIPLICATION

- OThe matrix chain product problem is to find the order of multiplying the matrices that minimizes the total number of multiplications used.
- We will use dynamic programming approach to find a solution for the matrix chain product problem.



## MATRIX CHAIN MULTIPLICATION

OThe matrix chain product algorithm.

$$(r_1 \boldsymbol{\times} r_2) \quad (r_2 \boldsymbol{\times} r_3) \quad (r_3 \boldsymbol{\times} r_4) \quad \dots \quad (r_{n-1} \boldsymbol{\times} r_n) \quad \ (r_n \boldsymbol{\times} r_{n+1})$$

$$M_1$$
  $M_2$   $M_3$  ...  $M_{n-1}$   $M_n$ 

- First: there is only one way to compute  $M_1M_2$  which takes  $r_1 \times r_2 \times r_3$  multiplications,  $M_2M_3$  which takes  $r_2 \times r_3 \times r_4$  multiplications,..., and  $M_{n-1}M_n$  which takes  $r_{n-1} \times r_n \times r_{n+1}$  multiplications.
- Next: We store these costs in a TABLE.



#### MATRIX CHAIN MULTIPLICATION

 Next: We find the best way to multiply successive triples:

$$(M_1M_2M_3),(M_2M_3M_4),..,(M_{n-2}M_{n-1}M_n).$$

The minimum cost of  $(M_1M_2M_3)$  is the smaller of the cost of

- 1.  $((M_1M_2)M_3) \rightarrow \text{the cost of } (M_1M_2) \text{ plus } r_1 \times r_3 \times r_4$
- 2.  $(M_1(M_2M_3)) \rightarrow \text{the cost of } (M_2M_3) \text{ plus } r_1 \times r_2 \times r_4$



#### MATRIX CHAIN MULTIPLICATION

- O When finding the costs of  $((M_1M_2)M_3)$  and  $(M_1(M_2M_3))$ , we do not re-compute the costs of  $(M_1M_2)$  and  $(M_2M_3)$  but simply find them from the **TABLE**.
- O The minimum costs of  $(M_1M_2M_3)$ ,  $(M_2M_3M_4),...,(M_{n-2}M_{n-1}M_n)$  are also kept in the **TABLE**.

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#### MATRIX CHAIN MULTIPLICATION

O Minimum Costs TABLE.



#### MATRIX CHAIN MULTIPLICATION

- In general, we find the best way to compute  $(M_iM_{i+1}...M_{i+j})$  by finding the minimum cost of computing  $(M_iM_{i+1}...M_{k-1})(M_k...M_{i+j})$  for i < k < j.
- The cost of  $(M_iM_{i+1}...M_{k-1})(M_k...M_{i+j})$  is the sum of the cost of  $(M_iM_{i+1}...M_{k-1})$ , the cost of  $(M_k...M_{i+j})$ , and  $r_i \times r_k \times r_{i+j+1}$ .

#### MATRIX CHAIN MULTIPLICATION

- The cost of  $(M_iM_{i+1}...M_{k-1})$  and the cost of  $(M_k...M_{i+j})$  are found from the **TABLE**.
- The minimum cost of  $(M_iM_{i+1}...M_{i+j})$  is kept in the **TABLE**.



#### MATRIX CHAIN MULTIPLICATION

• The pseudo-code is:

```
def MATRIX-CHAIN-ORDER (r):

// r- list of matrices dimensions.

// m - table of costs, s - optimal cost index table.

n = r.length \cdot 1

m = matrix (1...n, 1...n), s = matrix (1...n-1, 2...n)

for i = 1 to n \cdot m[i,i] = 0

for l = 2 to n \cdot m[i,i] = 0

for l = 1 to n - l + 1:

j = i + l - 1

m[i,j] = \infty

for k = i to j - 1:

q = m[i,k] + m[k+1,j] + r_{i+1}r_kr_j

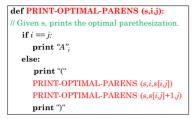
if q < m[i,j] : m[i,j] = q \cdot s[i,j] = k

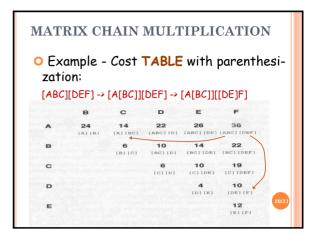
return m \cdot s
```



#### MATRIX CHAIN MULTIPLICATION

• The pseudo-code for printing the optimal parenthesization is:





#### THE KNAPSACK PROBLEM

- O A thief robbing a safe finds it filled with N types of items of varying size and value, but has only a small knapsack of capacity M to use to carry the goods.
- The knapsack problem is to find the combination of items which the thief should choose for his knapsack in order to maximize the total value of all the items it takes.

# 

#### THE KNAPSACK PROBLEM

- The thief can take:
  - 5 A's that make total value of 20 (space of 2 unused)
  - 1 D and 1 E that make total value of 24 (space of 3 unused)
- o But how to maximize the total value?



# THE KNAPSACK PROBLEM

- There are many commercial situations in which a solution to the knapsack problem could be important, for example a shipping company wishing to find the best way to load a truck or cargo plane, etc.
- $\circ$  In the dynamic-programming solution to the knapsack problem, we calculate the **best** combination for all knapsacks of sizes up to M.

#### THE KNAPSACK PROBLEM

- In this case, cost[k] is the highest value that can be achieved with a knapsack of capacity k and best[k] is the last item that was added to achieve that maximum.
- First, we calculate the best we can do for all knapsack sizes when only items of type A are taken, then we calculate the best that we can do when only A's and B's are taken, etc.

#### THE KNAPSACK PROBLEM

- O Suppose an item j is chosen for the knapsack.
- Then the best value that could be achieved for the total would be:

  val[j] + cost[k size[j]].
- If this value exceeds the best value that can be achieved without an item j, then we update cost[k] and best[k].

#### THE KNAPSACK PROBLEM

O Costs table for the previous example

```
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
                4 4 4 8 8 8 12 12 12 16 16 16 20 20 20
   best[k]
                A A A A A A A A A A A A
1=2
                     5 8 9 10 12 13 14 16 17 18 20 21 22
   best[k]
               ABBABBABBABBABB
                4 5 5 8 10 10 12 14 15 16 18 20 20 22 24
   best[k]
               ABBACBACCACCACC
               4 5 5 8 10 11 12 14 15 16 18 20 21 22 24

A B B A C D A C C A C C D C C
   cost [k]
  best[k]
               4 5 5 8 10 11 13 14 15 17 18 20 21 23 24

A B B A C D E C C E C C D E C
   cost[k]
```

#### THE KNAPSACK PROBLEM

- The first pair of lines shows the best that can be done with only A's.
- The second pair of lines shows the best that can be done with only A's and B's, etc.
- The highest value that can be achieved with a knapsack of size 17 is 24.

## THE KNAPSACK PROBLEM

 The pseudo-code to calculate the cost[k] and best[k].

```
\begin{aligned} &\textbf{for } j = 1 \textbf{ to } n: \\ &\textbf{for } i = 1 \textbf{ to } m: \\ &\textbf{ if } i >= size[j]: \\ &\textbf{ if } cost[i] < cost[i-size[j]] + val[j] \\ &cost[i] = cost[i-size[j]] + val[j]) \\ &best[i] = j \end{aligned}
```



## THE KNAPSACK PROBLEM

- oThe knapsack problem is easily solved for small size M, but the computing time may become unacceptable when the M is sufficiently large.
- This method does NOT work if M and the sizes or values are real numbers instead of integers.

