

Dynamic Programming



Outline and Reading

- ◆ Matrix Chain-Product (§5.3.1)
- ◆ The General Technique (§5.3.2)
- ◆ 0-1 Knapsack Problem (§5.3.3)



Matrix Chain-Products

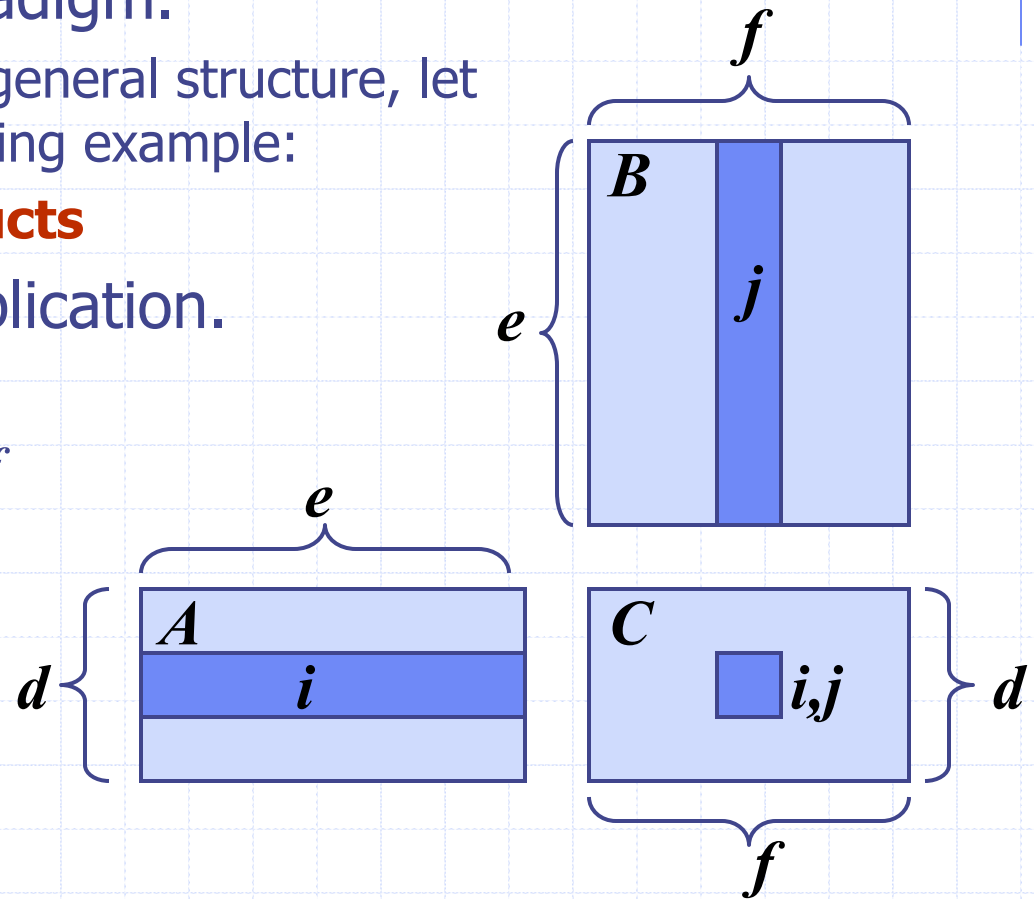


- ◆ **Dynamic Programming** is a general algorithm design paradigm.
 - Rather than give the general structure, let us first give a motivating example:
 - **Matrix Chain-Products**

◆ Review: Matrix Multiplication.

- $C = A * B$
- A is $d \times e$ and B is $e \times f$
- $O(d \cdot e \cdot f)$ time

$$C[i, j] = \sum_{k=0}^{e-1} A[i, k] * B[k, j]$$



Matrix Chain-Products



◆ Matrix Chain-Product:

- Compute $A = A_0 * A_1 * \dots * A_{n-1}$
- A_i is $d_i \times d_{i+1}$
- Problem: How to parenthesize?

◆ Example

- B is 3×100
- C is 100×5
- D is 5×5
- $(B * C) * D$ takes $1500 + 75 = 1575$ ops
- $B * (C * D)$ takes $1500 + 2500 = 4000$ ops

Enumeration Approach

◆ Matrix Chain-Product Alg.:

- Try all possible ways to parenthesize $A=A_0*A_1*\dots*A_{n-1}$
- Calculate number of ops for each one
- Pick the one that is best

◆ Running time:

- The number of parenthesizations is equal to the number of binary trees with n nodes
- This is **exponential!**
- It is called the Catalan number, and it is almost 4^n .
- This is a terrible algorithm!





Greedy Approach

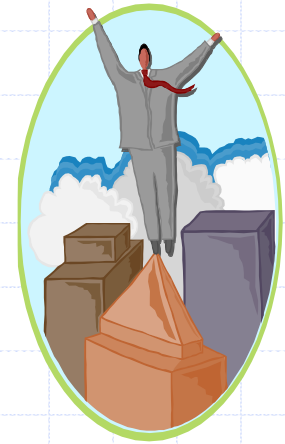
- ◆ Idea #1: repeatedly select the product that uses (up) the most operations.
- ◆ Counter-example:
 - A is 10×5
 - B is 5×10
 - C is 10×5
 - D is 5×10
 - Greedy idea #1 gives $(A*B)*(C*D)$, which takes $500+1000+500 = 2000$ ops
 - $A*((B*C)*D)$ takes $500+250+250 = 1000$ ops

Another Greedy Approach



- ◆ Idea #2: repeatedly select the product that uses the fewest operations.
- ◆ Counter-example:
 - A is 101×11
 - B is 11×9
 - C is 9×100
 - D is 100×99
 - Greedy idea #2 gives $A*((B*C)*D)$, which takes $109989+9900+108900=228789$ ops
 - $(A*B)*(C*D)$ takes $9999+89991+89100=189090$ ops
- ◆ The greedy approach is not giving us the optimal value.

“Recursive” Approach



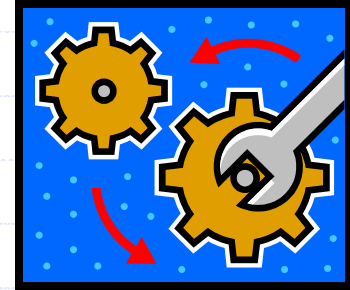
◆ Define **subproblems**:

- Find the best parenthesization of $A_i * A_{i+1} * \dots * A_j$.
- Let $N_{i,j}$ denote the number of operations done by this subproblem.
- The optimal solution for the whole problem is $N_{0,n-1}$.

◆ **Subproblem optimality**: The optimal solution can be defined in terms of optimal subproblems

- There has to be a final multiplication (root of the expression tree) for the optimal solution.
- Say, the final multiply is at index i : $(A_0 * \dots * A_i) * (A_{i+1} * \dots * A_{n-1})$.
- Then the optimal solution $N_{0,n-1}$ is the sum of two optimal subproblems, $N_{0,i}$ and $N_{i+1,n-1}$ plus the time for the last multiply.
- If the global optimum did not have these optimal subproblems, we could define an even better “optimal” solution.

Characterizing Equation

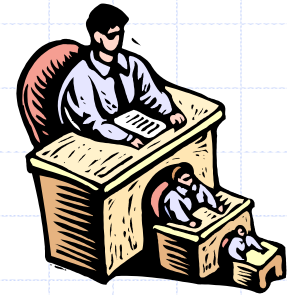


- ◆ The global optimal has to be defined in terms of optimal subproblems, depending on where the final multiply is at.
- ◆ Let us consider all possible places for that final multiply:
 - Recall that A_i is a $d_i \times d_{i+1}$ dimensional matrix.
 - So, a characterizing equation for $N_{i,j}$ is the following:

$$N_{i,j} = \min_{i \leq k < j} \{ N_{i,k} + N_{k+1,j} + d_i d_{k+1} d_{j+1} \}$$

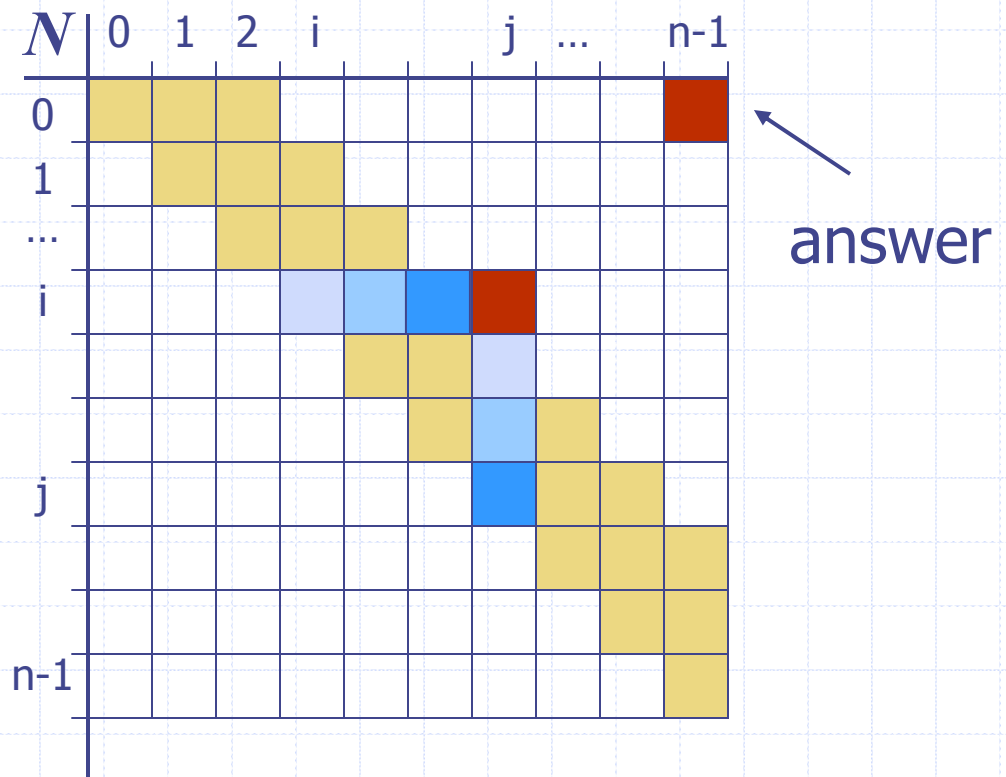
- ◆ Note that subproblems are not independent—the **subproblems overlap**.

Dynamic Programming Algorithm Visualization

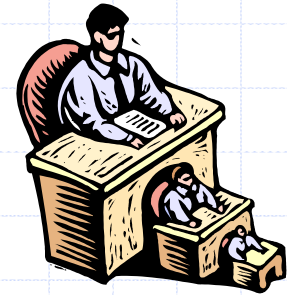


- ◆ The bottom-up construction fills in the N array by diagonals
- ◆ $N_{i,j}$ gets values from previous entries in i-th row and j-th column
- ◆ Filling in each entry in the N table takes $O(n)$ time.
- ◆ Total run time: $O(n^3)$
- ◆ Getting actual parenthesization can be done by remembering "k" for each N entry

$$N_{i,j} = \min_{i \leq k < j} \{N_{i,k} + N_{k+1,j} + d_i d_{k+1} d_{j+1}\}$$



Dynamic Programming Algorithm



- ◆ Since subproblems overlap, we don't use recursion.
- ◆ Instead, we construct optimal subproblems "bottom-up."
- ◆ $N_{i,i}$'s are easy, so start with them
- ◆ Then do problems of "length" 2,3,... subproblems, and so on.
- ◆ Running time: $O(n^3)$

Algorithm *matrixChain(S)*:

Input: sequence S of n matrices to be multiplied

Output: number of operations in an optimal parenthesization of S

for $i \leftarrow 1$ **to** $n - 1$ **do**

$N_{i,i} \leftarrow 0$

for $b \leftarrow 1$ **to** $n - 1$ **do**

{ $b = j - i$ is the length of the problem }

for $i \leftarrow 0$ **to** $n - b - 1$ **do**

$j \leftarrow i + b$

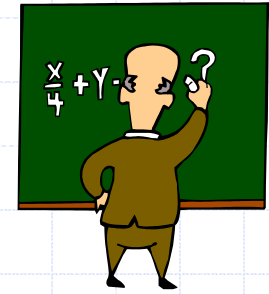
$N_{i,j} \leftarrow +\infty$

for $k \leftarrow i$ **to** $j - 1$ **do**

$N_{i,j} \leftarrow \min \{ N_{i,j}, N_{i,k} + N_{k+1,j} + d_i d_{k+1} d_{j+1} \}$

return $N_{0,n-1}$

The General Dynamic Programming Technique



- ◆ Applies to a problem that at first seems to require a lot of time (possibly exponential), provided we have:
 - **Simple subproblems:** the subproblems can be defined in terms of a few variables, such as j , k , l , m , and so on.
 - **Subproblem optimality:** the global optimum value can be defined in terms of optimal subproblems
 - **Subproblem overlap:** the subproblems are not independent, but instead they overlap (hence, should be constructed bottom-up).

The 0/1 Knapsack Problem



- ◆ Given: A set S of n items, with each item i having
 - w_i - a positive weight
 - b_i - a positive benefit
- ◆ Goal: Choose items with maximum total benefit but with weight at most W .
- ◆ If we are **not** allowed to take fractional amounts, then this is the **0/1 knapsack problem**.
 - In this case, we let T denote the set of items we take

- Objective: maximize
$$\sum_{i \in T} b_i$$

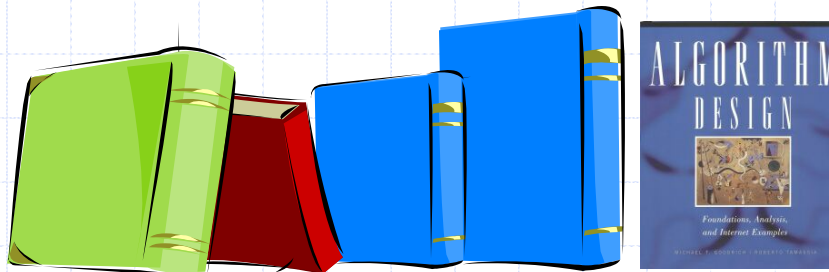
- Constraint:
$$\sum_{i \in T} w_i \leq W$$

Example



- ◆ Given: A set S of n items, with each item i having
 - b_i - a positive "benefit"
 - w_i - a positive "weight"
- ◆ Goal: Choose items with maximum total benefit but with weight at most W .

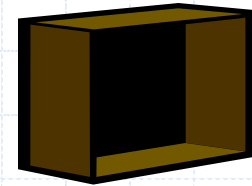
Items:



1 2 3 4 5

Weight:	4 in	2 in	2 in	6 in	2 in
Benefit:	\$20	\$3	\$6	\$25	\$80

"knapsack"



box of width 9 in

Solution:

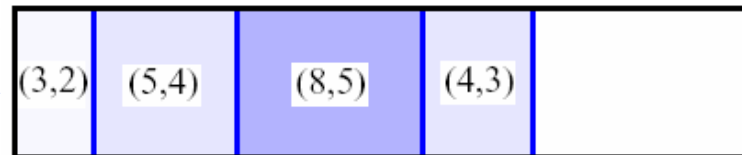
- item 5 (\$80, 2 in)
- item 3 (\$6, 2in)
- item 1 (\$20, 4in)

A 0/1 Knapsack Algorithm, First Attempt

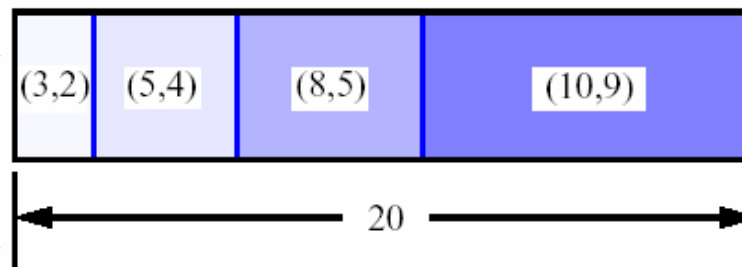


- ◆ S_k : Set of items numbered 1 to k .
- ◆ Define $B[k]$ = best selection from S_k .
- ◆ Problem: does not have subproblem optimality:
 - Consider set $S = \{(3,2), (5,4), (8,5), (4,3), (10,9)\}$ of (benefit, weight) pairs and total weight $W = 20$

Best for S_4 :



Best for S_5 :



A 0/1 Knapsack Algorithm, Second Attempt



- ◆ S_k : Set of items numbered 1 to k .
- ◆ Define $B[k, w]$ to be the best selection from S_k with weight at most w
- ◆ Good news: this does have subproblem optimality.

$$B[k, w] = \begin{cases} B[k-1, w] & \text{if } w_k > w \\ \max \{B[k-1, w], B[k-1, w - w_k] + b_k\} & \text{else} \end{cases}$$

- ◆ I.e., the best subset of S_k with weight at most w is either
 - the best subset of S_{k-1} with weight at most w or
 - the best subset of S_{k-1} with weight at most $w - w_k$ plus item k

0/1 Knapsack Algorithm



$$B[k, w] = \begin{cases} B[k-1, w] & \text{if } w_k > w \\ \max\{B[k-1, w], B[k-1, w-w_k] + b_k\} & \text{else} \end{cases}$$

- ◆ Recall the definition of $B[k, w]$
- ◆ Since $B[k, w]$ is defined in terms of $B[k-1, *]$, we can use two arrays instead of a matrix
- ◆ Running time: $O(nW)$.
- ◆ Not a polynomial-time algorithm since W may be large
- ◆ This is a **pseudo-polynomial** time algorithm

Algorithm *01Knapsack*(S, W):

Input: set S of n items with benefit b_i and weight w_i ; maximum weight W

Output: benefit of best subset of S with weight at most W

let A and B be arrays of length $W + 1$

for $w \leftarrow 0$ **to** W **do**

$B[w] \leftarrow 0$

for $k \leftarrow 1$ **to** n **do**

copy array B into array A

for $w \leftarrow w_k$ **to** W **do**

if $A[w-w_k] + b_k > A[w]$ **then**

$B[w] \leftarrow A[w-w_k] + b_k$

return $B[W]$