

Math 182 Lecture 12

Chapter 6 Dynamic Programming cont.

Recall: dynamic programming is often useful for optimization problems i.e. where you have many possible configurations, want to find one w/ best "value".

- (1) Characterize structure of optimal solution.
- (2) Recursively define value of optimal solution.
- (3) Compute value of optimal solution either:
 - (a) recursively w/ memoization
 - (b) iteratively solve subproblems in a bottom-up manner.
- (4) Construct an optimal solution from computed information.

§ 6.2 Matrix-chain multiplication

Suppose we want to evaluate

$$A_1 A_2 \cdots A_n$$

there are multiple ways to evaluate:

E.g. $n=4$ $A_1 A_2 A_3 A_4$

5 ways to evaluate:

$$\begin{array}{c} A_1 | (A_2 (A_3 A_4)) \\ \hline A_1 | ((A_2 A_3) A_4) \\ \hline (A_1 A_2) | (A_3 A_4) \\ \hline (A_1 (A_2 A_3)) | A_4 \\ \hline ((A_1 A_2) A_3) | A_4 \end{array}$$

A $m \times n$ $A \times B$ compatible if
 B $p \times q$ $n = p$
 # columns of A = # rows of B .

$$A_{m \times n} \times B_{n \times q} = C_{m \times q} \quad c_{ij} = \sum_{k=1}^n a_{ik} b_{kj}$$

MATRIX-MULTIPLY(A, B)

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1 if  $A.\text{columns} \neq B.\text{rows}$ 
2   error "incompatible dimensions"
3 else let  $C$  be a new  $A.\text{rows} \times B.\text{columns}$  matrix
4   for  $i = 1$  to  $A.\text{rows}$ 
5     for  $j = 1$  to  $B.\text{columns}$ 
6        $c_{ij} = 0$ 
7       for  $k = 1$  to  $A.\text{columns}$ 
8          $c_{ij} = c_{ij} + a_{ik} \cdot b_{kj}$ 
9   return  $C$ 
```

Total number of scalar multiplications =
 $A.\text{rows} \times B.\text{columns} \times A.\text{columns}$

$$\rightarrow mnq$$

Example $\langle A_1, A_2, A_3 \rangle$
 $10 \times 100 \quad 100 \times 5 \quad 5 \times 50$

better $\rightarrow (A_1 A_2) A_3 \rightsquigarrow 7500 \text{ sc.mults.}$

worse $\rightarrow A_1 (A_2 A_3) \rightsquigarrow 75000 \text{ sc.muls}$

The **matrix-chain multiplication problem** is as follows: given a chain $\langle A_1, A_2, \dots, A_n \rangle$ of n matrices, where for $i = 1, 2, \dots, n$, matrix A_i has dimension $p_{i-1} \times p_i$, fully parenthesize the product $A_1 A_2 \cdots A_n$ in a way that minimizes the number of scalar multiplications.

Really this is a problem about
 $P = \langle P_0, P_1, \dots, P_n \rangle$. not A_1, \dots, A_n .

Count # of parenthesizations:

Let $P(n)$ be # of ways to parenthesize
 $A_1 \cdots A_n$.

$$n=1 \quad P(n)=1$$

Sps $n \geq 2$ $A_1 \cdots A_n$
 to choose parenthesization, choose
 index to split at
 $(A_1 \cdots A_k)(A_{k+1} \cdots A_n) \quad 1 \leq k \leq n-1$

and choose a parenthesization for $A_1 \cdots A_k$
 and $A_{k+1} \cdots A_n$ recursively.

$$\leadsto P(n) = \sum_{k=1}^{n-1} P(k) P(n-k)$$

$$P(n) = \begin{cases} 1 & \text{if } n=1 \\ \sum_{k=1}^{n-1} P(k) P(n-k) & \text{if } n \geq 2. \end{cases}$$

$P(n)$ seq is called the Catalan numbers

$$P(n) = \mathcal{O}\left(\frac{4^n}{n^{3/2}}\right)$$

easier: $P(n) = \mathcal{O}(2^n)$ Exponential \rightarrow bad

Let's design dyn. prog. sol.

Step 1: Structure of optimal parenthesization
notation: $A_{i..j} := A_i \dots A_j$

Sps $i < j$ and we have an optimal paren. for $A_{i..j}$.

there must be some index k
s.t. $1 \leq k \leq n-1$ and

$$A_{i..j} = (A_{i..k})(A_{k+1..j})$$

↑ ↑
some paren. here.

Must use optimal parenthesizations
by swapping out argument.

Step 2: Recursive solution.

Let $m[i..j] :=$ minimal # of scalar multiplications needed
 $1 \leq i \leq j \leq n$. for some paren. of $A_{i..j}$.

Base case: $i = j$.

$$m[i, i] = 0$$

$$A_i \quad p_{i-1} \times p_i$$

Suppose $i < j$, Then there will be some k as above where

$$A_{i..j} = (\underbrace{A_{i..k}}_T)(\underbrace{A_{k+1..j}}_T)$$

$$m[i, j] = m[i, k] + m[k+1, j] + p_{i-1} p_k p_j$$

$$m[i, j] = \begin{cases} 0 & \text{if } i = j \\ \min_{i \leq k \leq j-1} \{m[i, k] + m[k+1, j] + p_{i-1} p_k p_j\} & \text{otherwise} \end{cases}$$

$\rightarrow m[i, j]$ will be array of optimal sols to subproblems.

For purposes of reconstructing answer, will also store:

$i < j \quad s[i, j] = k$ where k is s.t.
 $i \leq k \leq j-1$ and k achieves minimum in recursive formula.

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

$$j-k-1, k-i < j-i$$

Subproblem of certain chain length depends only on subproblems of smaller lengths.

$A_1 A_2 \dots A_6$

j	1	2	3	4	5	i
6	3	3	3	5	5	
5	3	3	3	4		
4	3	3	3			
3	1	2				
2	1					

$$A_{1..6} \quad s[1..6] = 3$$

$$(A_{1..3} \quad A_{4..6}) \quad s[1..3] = 1 \quad 2$$

$$\left((A_1 (A_2 A_5)) ((A_4 A_5) A_6) \right) s[4..6] = 5 \leftarrow$$

Step 3 Compute optimal costs:

$$A_1, \dots, A_n \quad A_i: p_{i-1} \times p_i \\ P = \langle p_0, p_1, \dots, p_n \rangle$$

MATRIX-CHAIN-ORDER(p)

```
1   $n = p.length - 1$ 
2  let  $m[1..n, 1..n]$  and  $s[1..n-1, 2..n]$  be new tables
3  for  $i = 1$  to  $n$ 
4     $m[i, i] = 0$ 
5  for  $l = 2$  to  $n$  //  $l$  is the chain length
6    for  $i = 1$  to  $n-l+1$ 
7       $j = i + l - 1$ 
8       $m[i, j] = \infty$ 
9      for  $k = i$  to  $j-1$ 
10         $q = m[i, k] + m[k+1, j] + p_{i-1} p_k p_j$ 
11        if  $q < m[i, j]$ 
12           $m[i, j] = q$ 
13           $s[i, j] = k$ 
14 return  $m$  and  $s$ 
```

Lines 1-4 create $m[i, j]$, $s[i, j]$ and initialize $m[i, i] = 0 \forall i$.

For loop of line 5-13 iterate through all chain lengths from smallest to largest.

For loop line 6-13 iterate through all pairs i, j w/ chain length l .

In lines 8-13 apply recurrence relation to store $m[i, j]$ and $s[i, j]$.

Running time is $\mathcal{O}(n^3)$, actually $\Theta(n^3)$

Step 4: Reconstructing an 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 ")"
```

If $i = j$ print " A_i " since only one matrix

O/w print

"($A_{i \dots s[i, i]}$ $A_{s[i, i] + 1 \dots j}$)"

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recursively these will be optimal
parenthesizations for corresponding
subproducts.

Chapter 7 Greedy Algorithms

Greedy algorithms also work sometimes for optimization problems.

A greedy algorithm is one where you can make locally optimal choice in the hopes it leads to globally optimal solution.

§7.1 Activity-selection problem

Sps you have to schedule a common resource (e.g. a room), you receive large # of requests
goal: want to accomodate most # of distinct requests as possible.

Specifically:

$S = \{a_1, \dots, a_n\}$ of proposed activities
for each activity have $\underset{\text{start time}}{s_i}$ $\underset{\text{finish time}}{f_i}$ w/ $0 \leq s_i < f_i < \infty$
 a_i takes place during $[s_i, f_i]$

We say a_i and a_j compatible if $[s_i, f_i] \cap [s_j, f_j] = \emptyset$

equivalently $f_i \leq s_j$ or $f_j \leq s_i$.

The **activity-selection problem**, we want to find a maximum-size subset of $S = \{a_1, \dots, a_n\}$ of mutually-compatible activities. Note that we want to maximize the *number* of activities scheduled, not necessarily the total *duration* of the activities which are scheduled.

For convenience, will assume activities are listed in increasing order of finish time:

$$f_1 \leq f_2 \leq f_3 \leq \dots \leq f_{n-1} \leq f_n$$

E.g.

i	1	2	3	4	5	6	7	8	9	10	11
s_i	1	3	0	5	3	5	6	8	8	2	12
f_i	4	5	6	7	8	8	10	11	12	14	16

$\{a_3, a_9, a_{11}\}$ mut. comp.

$\{a_1, a_4, a_8, a_{11}\}$ mut. comp. \leftarrow optimal

$\{a_2, a_7, a_9, a_{11}\}$ mut. comp. \leftarrow sols.