CSE 100: Algorithm Design and Analysis Chapter 15: Dynamic Programming

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Outline

- ▶ What is DP?
- ► How does it work?
- How do we analyze the running time?

Examples: Fibonacci numbers, Rod cutting, Matrix chain multiplication, Longest common subsequence.

Sample Questions

- Derive a recursion for a given problem.
- Does the naive implementation of the recursion have an exponential running time?
- Solve the following problem using DP. Bottom-up vs. Top-down.
- Translate a given recursion into a DP.
- Analyze the running time of a given DP.
- Find an optimal solution by a traceback method.

Examples: Fibonacci numbers, Rod cutting, Matrix chain multiplication, Longest common subsequence.

Dynamic Programming

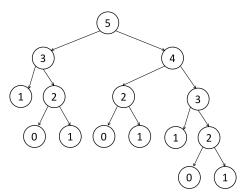
- Not a specific algorithm, but a technique.
- Not actual computer programming
- Used for an optimization (minimization or maximization) problem whose recursion makes lots of overlapping recursive calls.
 - ▶ Optimization problem: Find a solution with the optimal value.

The Fibonacci Sequence is 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, \cdots . Formally, f(0) = 0, f(1) = 1 and f(i) = f(i-1) + f(i-2) for all $i \ge 2$, where f(i) denotes the ith Fibonacci number. Would like to compute nth Fib number.

A naive implementation:

The Fibonacci Sequence is 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, \cdots . Formally, f(0) = 0, f(1) = 1 and f(i) = f(i-1) + f(i-2) for all $i \ge 2$, where f(i) denotes the ith Fibonacci number. Would like to compute nth Fib number.

Recursion tree of the naive implementation:



DP via bottom-up: Pseudocode

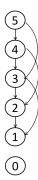
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```
bottom up:
int F(n)
  Array A[0 ... n]
  A[0] = 0, A[1] = 1
  for i = 2; i <= n; i++
       A[i] = A[i-1] + A[i-2]
  return A[i]</pre>
```

DP via bottom-up

The Fibonacci Sequence is 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, \cdots . Formally, f(0) = 0, f(1) = 1 and f(i) = f(i-1) + f(i-2) for all $i \ge 2$, where f(i) denotes the ith Fibonacci number. Would like to compute nth Fib number.

Dependency graph:



DP via top-down with memoization

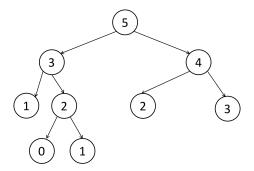
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```
top down:
int F(n)
  Array A[0 ... n]
  A[0] = 0, A[1] = 1
  A[2] = A[3] = ... = A[n] = - infinity
  return Aux-F(A, n)

int Aux-F(n)
  if A[n] >= 0 return A[n]
  A[n] = Aux-F(A, n-1) + Aux-F(A, n-2)
  return A[n]
```

DP via top-down with memoization

The Fibonacci Sequence is 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, \cdots . Formally, f(0) = 0, f(1) = 1 and f(i) = f(i-1) + f(i-2) for all $i \ge 2$, where f(i) denotes the ith Fibonacci number. Would like to compute nth Fib number.



Cut a given steel rod into pieces of integer lengths in order to maximize the revenue. Cutting is free. Input:

- ▶ *n*: the length of the given rod
- ▶ p_i : the price of a rod/piece of length i, $1 \le p_i \le n$. $(p_0 = 0)$.

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1. Interpretation as an Optimization Problem

- This is an optimization problem.
- A feasible solution is a cut of the given rod into pieces of integer lengths.
- Each solution yields a certain profit.
- ► The objective is the profit, which is to be maximized.
- In general, a solution maximizing (or minimizing) the objective is called an optimum solution. The maximum (or minimum) objective is called the optimum. There can be multiple optimum solutions, but the optimum is unique.

Let r_n denote the optimum for rod of length n, i.e., the max profit we can get out of a rod of length n.

1. Interpretation as an Optimization Problem

Let r_n denote the optimum for rod of length n, i.e. the max profit we can get out of a rod of length n.

```
r_1 = 1 from solution 1 = 1 (no cuts),

r_2 = 5 from solution 2 = 2 (no cuts),

r_3 = 8 from solution 3 = 3 (no cuts),

r_4 = 10 from solution 4 = 2 + 2,

r_5 = 13 from solution 5 = 2 + 3,

r_6 = 17 from solution 6 = 6 (no cuts),

r_7 = 18 from solution 7 = 1 + 6 or 7 = 2 + 2 + 3,

r_8 = 22 from solution 8 = 2 + 6,

r_9 = 25 from solution 9 = 3 + 6,

r_{10} = 30 from solution 10 = 10 (no cuts).
```

2. Finding a Recursion to Compute the Optimum

Let r_n denote the optimum for rod of length n, i.e. the max profit we can get out of a rod of length n.

Let's first try to find a recursion to compute r_n . Then, we will try to find a solution that achieves r_n .

$$r_j = \max_{1 \le i \le j} (p_i + r_{j-i}) \text{ if } j \ge 1$$
$$r_0 = 0$$

Interpretation: Here, i is the length of the first piece.

2. Finding a Recursion to Compute the Optimum: Pseudocode

```
CUT-ROD(p, n)

1 if n == 0

2 return 0

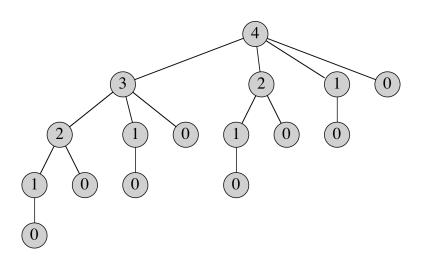
3 q = -\infty

4 for i = 1 to n

5 q = \max(q, p[i] + \text{CUT-ROD}(p, n - i))

6 return q
```

3. Identifying Redundancies in the Recursion Tree and Deciding What to Store



4. USE DP for Speed-up: Bottom-up DP description in words

(Let
$$p[i] = p_i$$
 denote the price of a rod of length i)
Set up a DP table with entries $r[i]$ where $0 \le i \le n$
 $r[0] = 0$
Compute $r[1], r[2], ..., r[n]$ in this order using the recursion,
 $r[j] = \max_{1 \le i \le j} (p[i] + r[j-i])$
Return $r[n]$ as the optimum

length i	0	1	2	3	4	5	6
pi	0	1	5	8	9	10	17
ri							

4. USE DP for Speed-up: Bottom-up DP pseudocode

```
BOTTOM-UP-CUT-ROD(p, n)
   let r[0...n] be a new array
2 r[0] = 0
  for j = 1 to n
       q = -\infty
5
       for i = 1 to j
           q = \max(q, p[i] + r[j-i])
       r[j] = q
   return r[n]
```

5. RT Analysis

```
(Let p[i] = p_i denote the price of a rod of length i)

Set up a DP table with entries r[i] where 0 \le i \le n

r[0] = 0

Compute r[1], r[2], ..., r[n] in this order using the recursion,

r[j] = \max_{1 \le i \le j} (p[i] + r[j-i])

Return r[n] as the optimum.
```

Number of entires in the DP table to fill out:

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```

Number of entires in the DP table to fill out: *n*. Time needed to fill out each DP table entry:

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(Let p[i] = p_i denote the price of a rod of length i)

Set up a DP table with entries r[i] where 0 \le i \le n

r[0] = 0

Compute r[1], r[2], ..., r[n] in this order using the recursion,

r[j] = \max_{1 \le i \le j} (p[i] + r[j - i])

Return r[n] as the optimum.
```

Number of entires in the DP table to fill out: n. Time needed to fill out each DP table entry: O(n).

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(Let p[i] = p_i denote the price of a rod of length i)
Set up a DP table with entries r[i] where 0 \le i \le n
r[0] = 0
Compute r[1], r[2], ..., r[n] in this order using the recursion, r[j] = \max_{1 \le i \le j} (p[i] + r[j-i])
Return r[n] as the optimum.
```

Number of entires in the DP table to fill out: n. Time needed to fill out each DP table entry: O(n). Thus, we can compute the optimum, r_n in $n*O(n) = O(n^2)$ time.

6. Finding an Optimum Solution

Key idea: To store the length of the first piece in an optimum solution/cut.

$$r_j = \max_{1 \le i \le j} (p_i + r_{j-i}) \text{ if } j \ge 1$$
$$r_0 = 0$$

Let s_j be i such that $p_i + r_{j-i} = r_j$. In other words, s_j is the length of the first piece in a cut giving profit r_j .

6. Finding an Optimum Solution

Key idea: To store the length of the first piece in an optimum solution/cut.

```
EXTENDED-BOTTOM-UP-CUT-ROD (p, n)
    let r[0..n] and s[0..n] be new arrays
2 r[0] = 0
3 for j = 1 to n
4 q = -\infty
  for i = 1 to j
           if q < p[i] + r[j-i]
               q = p[i] + r[j-i]
8
               s[i] = i
9
        r[j] = q
    return r and s
10
```

6. Finding an Optimum Solution

```
PRINT-CUT-ROD-SOLUTION (p, n)

1 (r, s) = \text{EXTENDED-BOTTOM-UP-CUT-ROD}(p, n)

2 while n > 0

3 print s[n]

4 n = n - s[n]
```

Another DP solution: Top-down with memoization

Solve recursively, but store each result in a table.

To find the solution to a subproblem, first look in the table.

If the answer is there, use it.

Otherwise, compute the solution to the subproblem and store it in the table for future use.

Another DP solution: Top-down with memoization

```
MEMOIZED-CUT-ROD(p,n)

1 let r[0..n] be a new array

2 for i=0 to n

3 r[i]=-\infty

4 return MEMOIZED-CUT-ROD-AUX(p,n,r)
```

```
MEMOIZED-CUT-ROD-AUX(p, n, r)

1 if r[n] \ge 0

2 return r[n]

3 if n == 0

4 q = 0

5 else q = -\infty

6 for i = 1 to n

7 q = \max(q, p[i] + \text{MEMOIZED-CUT-ROD-AUX}(p, n - i, r))

8 r[n] = q

9 return q
```

Input: a sequence of *n* matrices, $A_1, A_2, ..., A_n$ where A_i is $p_{i-1} \times p_i$.

Output: fully parenthesize the product $A_1A_2 \cdots A_n$ such that the number of multiplications is minimized.

Definition: A product of matrices is fully parenthesized if it is a single matrix or the product of two fully parenthesized matrix produces that is surrounded by parentheses.

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Definition: A product of matrices is fully parenthesized if it is a single matrix or the product of two fully parenthesized matrix produces that is surrounded by parentheses.

Questions: Is the following produce fully parenthesized?

► A: Yes

► AB: No

► (*AB*): Yes

► (*AB*)*C*: No

Matrix multiplication recap

- ➤ To be able to multiply two matrices, A and B, it must be the case that # of A's columns = # of B's rows.
- ▶ If A is $p \times q$ and B is $q \times r$, we assume that AB requires exactly pqr multiplications (using the standard matrix multiplication method).
- ightharpoonup AB is $p \times r$.
- ▶ Matrix multiplication is associative, i.e. (AB)C = A(BC).
- ▶ 1 to 1 mapping between full parenthesization and tree representation.

Example

Input: a sequence of *n* matrices, $A_1, A_2, ..., A_n$ where A_i is $p_{i-1} \times p_i$.

Output: fully parenthesize the product $A_1A_2 \cdots A_n$ such that the number of multiplications is minimized.

Example: $A_1(10), A_2(100 \times 5), A_3(5 \times 50).$

Two possible ways of full parenthesizations:

- $(A_1A_2)A_3: 10 \cdot 100 \cdot 5 + 10 \cdot 5 \cdot 50 = 5000 + 2500 = 7500.$
- A₁(A_2A_3): 100 · 5 · 50 + 10 · 100 · 50 = 25000 + 50000 = 75000.

Side note: Catalan number

The number of full parenthesizations for the produce of n matrices is P(n), where

$$P(n) = \sum_{k=1}^{n-1} P(k)P(n-k)$$
 when $n \ge 2$ and $P(1) = 1$.

P(n) has a special name, nth Catalan number, which appears in various forms in many problems. $P(n) = \Omega(2^n)$.

1. Interpretation as an Optimization Problem

As usual, we will first try to compute the optimum, i.e. the minimum number of multiplications needed to compute the chain of products. So, the objective is the number of multiplications performed, which is to be minimized.

Then, we will find a full parenthesization achieving the optimum.

2. Finding a Recursion to Compute the Optimum

Let's consider the tree representation, which is more intuitive.

- 1. The highest level split induces two subproblems.
- Optimal solution comes from optimal solutions to the subproblems.
- 3. (We will need search for the best split).

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A natural subproblem is on $A_{i...j} := A_i A_{i+1} \cdots A_j$.

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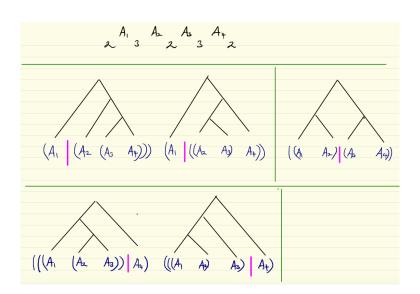
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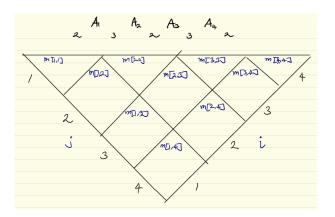
- 1. The highest level split induces two subproblems.
- Optimal solution comes from optimal solutions to the subproblems.
- 3. (We will need search for the best split).

A natural subproblem is on $A_{i...j}:=A_iA_{i+1}\cdots A_j$. So, define m[i,j] as the min number of multiplications needed to compute $A_{i...j}$. Our goal is now to compute m[1,n] fast.

2. Finding a Recursion to Compute the Optimum

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





3. Identifying Redundancies in the Recursion Tree and Deciding What to Store

This is left as an exercise.

4. USE DP for Speed-up: Bottom-up DP description in words; and 5. RT Analysis

```
Set up a DP table with entries m[i,j] where 1 \leq i \leq j \leq n. Compute m[i,j] using the recursion in the following order: m[1,1], m[2,2], ..., m[n,n]. m[1,2], m[2,3], ..., m[n-1,n]. m[1,3], m[2,4], ..., m[n-2,n]. ... m[1,n]. Return m[1,n] as the optimum.
```

Running time:

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Running time:

1. # of DP entries:

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Running time:

1. # of DP entries: $O(n^2)$

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- 1. # of DP entries: $O(n^2)$
- 2. RT for computing each entry:

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```

- 1. # of DP entries: $O(n^2)$
- 2. RT for computing each entry: O(n):
- 3. RT for computing the optimum: $O(n^3)$

Complete Description and RT Analysis of Bottom-up DP Algorithm for Computing the Optimum

To get full points for a DP algorithm (bottom-up) description, you must state

- 1. DP table entries
- 2. Recursion
- 3. In which order you compute the entries
- 4. What is the optimum?

Complete Description and RT Analysis of Bottom-up DP Algorithm for Computing the Optimum

To get full points for a DP algorithm (bottom-up) description, you must state

- 1. DP table entries
- 2. Recursion
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To get full points for analysis of RT, you must state

- 1. # of DP entries
- 2. RT for computing each entry
- 3. RT for computing the optimum

6. Finding an Optimum Solution

```
MATRIX-CHAIN-ORDER (p)
 1 \quad 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
        m[i,i] = 0
 5 for l = 2 to n // l is the chain length
        for i = 1 to n - l + 1
 6
            i = i + l - 1
            m[i, j] = \infty
             for k = i to i - 1
                 q = m[i,k] + m[k+1,j] + p_{i-1}p_kp_i
10
                 if q < m[i, j]
11
12
                     m[i, j] = q
13
                     s[i, i] = k
14
    return m and s
```

6. Finding an Optimum Solution

For each subproblem, remember where we should make the first split: Define s[i,j]: s[i,j] = k implies that there is an optimal solution for $A_{i...j}$ that is constructed by $A_{i...k} \times A_{k+1...j}$.

6. Finding an Optimum Solution

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Set up a DP table with entries m[i, j] where 1 \le i \le j \le n.
Compute m[i,j] using the recursion in the following order:
m[1,1], m[2,2], ..., m[n,n].
m[1,2], m[2,3], ..., m[n-1,n].
m[1, n]. (When computing m[i, j], we also compute s[i, j]; here
s[i,j] = k implies that there is an optimal solution for A_{i...i} that is
constructed by A_{i...k} \times A_{k+1...i}.)
             PRINT-OPTIMAL-PARENS (s, i, j)
                 if i == j
                    print "A"<sub>i</sub>
               else print "("
                     PRINT-OPTIMAL-PARENS (s, i, s[i, j])
                     PRINT-OPTIMAL-PARENS (s, s[i, j] + 1, j)
                     print ")"
```

Call Print-Optimal-Parens(s, 1, n)

6. Finding an Optimum Solution

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             3 else print "("
                     PRINT-OPTIMAL-PARENS (s, i, s[i, j])
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                     print ")"
```

Input: Two sequences, $X = \langle x_1, x_2, \dots, x_m \rangle$ and

 $Y = \langle y_1, y_2, \dots, y_n \rangle$

Goal: Find a longest subsequence common to both.

Def: Z is a subsequence of X iff Z can be obtained by deleting 0 or more elements from X.

Is the following a subsequence of BCBAE?

BB: Yes.

BCE: Yes.

AB: No.

- ► Each subproblem is computing a LCS of the prefixes of *X* and *Y*.
- $ightharpoonup X_i := \langle x_1, x_2, x_i \rangle$ and $Y_j := \langle y_1, y_2, y_j \rangle$
- ▶ Define $c[i,j] := \text{length of LCS of } X_i \text{ and } Y_j$

$$c[i,j] := \text{length of LCS of } X_i \text{ and } Y_i$$

$$c[i,j] = \begin{cases} 0 & \text{if } i = 0 \text{ or } j = 0 \\ c[i-1,j-1] + 1 & \text{if } i,j > 0 \text{ and } x_i = y_j \\ \max(c[i,j-1],c[i-1,j]) & \text{if } i,j > 0 \text{ and } x_i \neq y_j \end{cases}$$

The optimum is C[m, n].

X= ABCB DABE				Y=BDCABAE					C[is] by Table		
	i	0	B /	D 2	3	4 4	B 5	A 6	F 7		
\downarrow	0										
Α											
В	2										
С	3										
В	4										
D	5										
Α	6										
В	7										
F	8										

Compute length of LCS of X and Y:

Compute c[i,j], $0 \le i \le m$, $0 \le j \le n$ in row-major order using the recursion.

Return c[m, n].

Analysis

```
# of DP tables (subproblems): \Theta(mn). RT for computing each entry: \Theta(1). RT: \Theta(mn).
```

Memory usage: $\Theta(mn)$. If we only need to compute LCS length, we only need O(m+n) memory.

```
LCS-LENGTH(X, Y)
 1 m = X.length
 2 \quad n = Y.length
 3 let b[1..m, 1..n] and c[0..m, 0..n] be new tables
 4 for i = 1 to m
5 	 c[i,0] = 0
 6 for j = 0 to n
 7 c[0, i] = 0
 8 for i = 1 to m
         for j = 1 to n
10
             if x_i == y_i
                 c[i, j] = c[i-1, j-1] + 1
11
                 b[i, i] = "\\\\"
12
             elseif c[i-1, j] \ge c[i, j-1]
13
14
                 c[i, j] = c[i - 1, j]
15
                 b[i, j] = "\uparrow"
             else c[i, j] = c[i, j - 1]
16
                 b[i, i] = "\leftarrow"
17
18
    return c and b
```

```
PRINT-LCS(b, X, i, j)
   if i == 0 or j == 0
        return
3 if b[i, j] == "
"
        PRINT-LCS(b, X, i-1, j-1)
        print x_i
   elseif b[i, j] == "\uparrow"
        PRINT-LCS(b, X, i - 1, j)
   else PRINT-LCS(b, X, i, j - 1)
```