Lecture 16: Dynamic Programming - Pole Cutting COMS10007 - Algorithms

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Pole Cutting

Pole-cutting:

Given is a pole of length n



- The pole can be cut into multiple pieces of integral lengths
- A pole of length i is sold for price p(i), for some function p

Example:

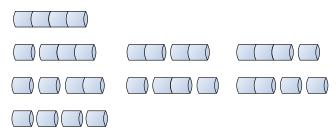


Pole Cutting (2)

Problem: Pole-Cutting

- **1 Input:** Price table p_i , for every $i \ge 1$, length n of initial pole
- **Quitput:** Maximum revenue r_n obtainable by cutting pole into smaller pieces

How many ways of cutting the pole are there?



Pole Cutting (3)

There are 2^{n-1} ways to cut a pole of length n.

Proof.

There are n-1 positions where the pole can be cut. For each position we either cut or we don't. This gives 2^{n-1} possibilities.

Problem:

- Find best out of 2^{n-1} possibilities
- We could diregard similar cuts, but we would still have an exponential number of possibilites
- A fast algorithm cannot try out all possibilities

Pole Cutting (4)

Notation

$$7 = 2 + 2 + 3$$

means we cut a pole of length 7 into pieces of lengths 2,2 and 3

Optimal Cut

• Suppose the optimal cut uses k pieces

$$n = i_1 + i_2 + \cdots + i_k$$

• Optimal revenue r_n :

$$r_n = p(i_1) + p(i_2) + \cdots + p(i_k)$$

Pole Cutting (5)

What are the optimal revenues r_i ?

$$r_1 = 1$$
 $1 = 1$
 $r_2 = 5$ $2 = 2$
 $r_3 = 8$ $3 = 3$
 $r_4 = 10$ $4 = 2 + 2$
 $r_5 = 13$ $5 = 2 + 3$
 $r_6 = 17$ $6 = 6$
 $r_7 = 18$ $7 = 2 + 2 + 3$
 $r_8 = 22$ $8 = 2 + 6$
 $r_9 = 25$ $9 = 3 + 6$
 $r_{10} = 30$ $10 = 10$

Optimal Substructure

Optimal Substructure

Consider an optimal solution to input length n

$$n = i_1 + i_2 + \cdots + i_k$$
 for some k

Then:

$$n-i_1=i_2+\cdots+i_k$$

is an optimal solution to the problem of size $n-i_1$

Computing Optimal Revenue r_n :

$$r_n = \max\{p_n, r_1 + r_{n-1}, r_2 + r_{n-2}, \dots, r_{n-1} + r_1\}$$

- p_n corresponds to the situation of no cut at all
- $r_i + r_{n-i}$: initial cut into two pieces of sizes i and n-i

Pole Cutting: Dynamic Programming Formulation

Simpler Recursive Formulation: Let $r_0 = 0$

$$r_n = \max_{1 \leq i \leq n} (p_i + r_{n-i}) .$$

Observe: Only one subproblem in this formulation

Example: n = 4

$$r_n = \max\{p_1 + r_3, p_2 + r_2, p_3 + r_1, p_4 + r_0\}$$

$$p_1 + r_3$$

$$p_2 + r_2$$

$$p_3 + r_1$$

$$\frac{p_4 + r_0}{(((())$$

Recursive Top-down Implementation

Recall:

$$r_n = \max_{1 \leq i \leq n} (p_i + r_{n-i})$$
 and $r_0 = 0$.

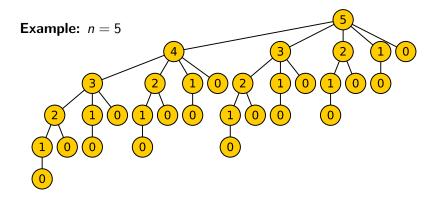
Direct Implementation:

```
Require: Integer n, Array p of length n with prices if n=0 then return 0 q \leftarrow -\infty for i=1\dots n do q \leftarrow \max\{q,p[i]+\text{Cut-Pole}(p,n-i)\} return q
```

Algorithm Cut-Pole(p, n)

How efficient is this algorithm?

Recursion Tree for CUT-POLE



Number Recursive Calls: T(n)

$$T(n) = 1 + \sum_{i=0}^{n-1} T(j) \text{ and } T(0) = 1$$

Solving Recurrence

How to Solve this Recurrence?

$$T(n) = 1 + \sum_{j=0}^{n-1} T(j)$$
 and $T(0) = 1$

- Substitution Method: Using guess $T(n) = O(c^n)$, for some c
- Trick: compute T(n) T(n-1)

$$T(n) - T(n-1) = 1 + \sum_{j=0}^{n-1} T(j) - \left(1 + \sum_{j=0}^{n-2} T(j)\right)$$

= $T(n-1)$, hence:
 $T(n) = 2T(n-1)$.

This implies $T(i) = 2^i$.

Discussion

Runtime of Cut-Pole

- Recursion tree has 2ⁿ nodes
- Each function call takes time O(n) (for-loop)
- Runtime of CUT-POLE is therefore $O(n2^n)$. $(O(2^n)$ can also be argued)

What can we do better?

- Observe: We compute solutions to subproblems many times
- Avoid this by storing solutions to subproblems in a table!
- This is a key feature of dynamic programming

Implementing the Dynamic Programming Approach

Top-down with memoization

- When computing r_i , store r_i in a table T (of size n)
- Before computing r_i again, check in T whether r_i has previously been computed

Bottom-up

- Fill table T from smallest to largest index
- No recursive calls are needed for this

Top-down Approach

```
Require: Integer n, Array p of length n with prices

Let r[0...n] be a new array

for i = 0...n do

r[i] \leftarrow -\infty

return Memoized-Cut-Pole-Aux(p, n, r)

Algorithm Memoized-Cut-Pole(p, n)
```

- Prepare a table r of size n
- Initialize all elements of r with $-\infty$
- Actual work is done in Memoized-Cut-Pole-Aux, table r is passed on to Memoized-Cut-Pole-Aux

Top-down Approach (2)

```
Require: Integer n, array p of length n with prices, array r of
  revenues
  if r[n] \ge 0 then
     return r[n]
  if n = 0 then
     q \leftarrow 0
  else
     q \leftarrow -\infty
     for i = 1 \dots n do
        q \leftarrow \max\{q, p[i] + \text{Memoized-Cut-Pole-Aux}(p, n - p[i])\}
        i, r)
  r[n] \leftarrow q
  return q
```

Algorithm Memoized-Cut-Pole-Aux(p, n, r)

Observe: If $r[n] \ge 0$ then r[n] has been computed previously

Bottom-up Approach

```
Require: Integer n, array p of length n with prices Let r[0 \dots n] be a new array r[0] \leftarrow 0 for j = 1 \dots n do q \leftarrow -\infty for i = 1 \dots j do q \leftarrow \max\{q, p[i] + r[j-i]\} return r[n]
```

Algorithm BOTTOM-UP-CUT-POLE(p, n)

Runtime: Two nested for-loops

$$\sum_{j=1}^{n} \sum_{i=1}^{j} O(1) = O(1) \sum_{j=1}^{n} \sum_{i=1}^{j} 1 = O(1) \sum_{j=1}^{n} j = O(1) \frac{n(n+1)}{2} = O(n^{2}).$$

Comclusion

Runtime of Top-down Approach $O(n^2)$

(please think about this!)

Dynamic Programming

- Solves a problem by combining subproblems
- Subproblems are solved at most once, store solutions in table
- If a problem exhibits optimal substructure then dynamic programming is often the right choice
- Top-down and bottom-up approaches have the same runtime