Program Structure and Algorithms

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Lecture 12

Agenda

- Administrative
 - HW5, PA2 will be out after today's class

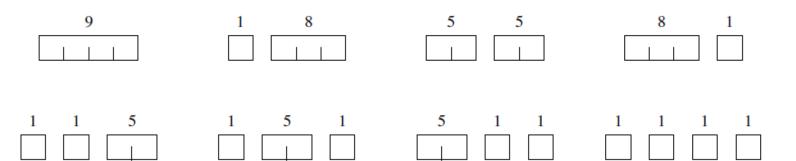
- Lecture
- Quiz

P5: Rod Cutting

- How to cut steel rods into pieces in order to maximize the revenue you can get? Each cut is free. Rod lengths are always an integer number of inches.
- Input: A length n (inches) and table of prices p_i , i = 1, 2, ..., n
- Output: Maximum revenue obtainable from rods whose lengths sum to n, computed as the sum of the prices for the individual rods
- Trivial solution: If p_n is very large, optimal solution needs no cuts, i.e., leave the rod as n inches long

Example

- After first n-1 inches, we can either cut or not .. 2^{n-1} ways
- 8 ways to cut a rod of length 4
 - best two 2 inches that yields a revenue of 5+5=10



Formulation

Let r_i be the max revenue for a rod of length i

By inspection

For n = 7, one opt sol makes a cut at $3in \rightarrow 2$ subproblems of lengths 3 and $4 \rightarrow$ solve both optimally.

The opt sol of length $4 \rightarrow 2 + 2 \rightarrow$ used in opt sol of length 7

i	r_i	optimal solution
1	1	1 (no cuts)
2	5	2 (no cuts)
3	8	3 (no cuts)
4	10	2 + 2
5	13	2 + 3
6	17	6 (no cuts)
7	18	1 + 6 or $2 + 2 + 3$
8	22	2 + 6

Optimal revenue r_n by taking max of

- p_n : revenue from not making a cut
- $r_1 + r_{n-1}$: max revenue from a rod 1 in and rod (n-1) in
- $r_2 + r_{n-2}$: max revenue from a rod 2in and rod (n-2)in, ...
- $r_{n-1} + r_1$

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

Formulation

Intuition: Every opt sol has a leftmost cut, i.e., there's some cut that gives a first piece of length i cut off the left end, and a remaining piece of length n-i on the right

Need to divide only the remainder, not the first piece

Sol with no cuts has first piece i = n with revenue p_n and remaining size of length 0 has revenue $r_0 = 0$ // base case

$$r_n = \max\{p_i + r_{n-i}, \forall i = 1 \dots n\}$$

Subproblem: Max revenue achievable by cutting a rod of length *i* off the left end

If you think of the rod demarcated at intervals of unit length, then entire rod is a sequence x[1:n]

Then, subproblem will be max revenue achievable by cutting x[1:i]

Naïve Recursive Top-Down Solution

What's the problem?

CUT-ROD calls itself repeatedly on solved subproblems!!!

CUT-ROD
$$(p, n)$$

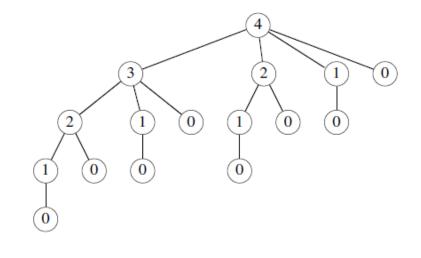
if $n == 0$
return 0
 $q = -\infty$
for $i = 1$ to n
 $q = \max \{q, p[i] + \text{CUT-ROD}(p, n - i)\}$
return q

Let's study for n = 4

Many repeated subproblems

Solves for subproblem for size 2 twice, for size 1 four times, for size 0 eight times!!!

$$T(n) = \begin{cases} 1, & \text{if } n = 0 \\ 1 + \sum_{j=0}^{n-1} T(j), & \text{if } n \ge 1 \end{cases} = O(2^n)$$



Subproblem Graphs

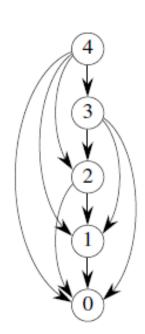
How to understand the dependency of subproblems? Directed graph

One vertex for each distinct subproblem

Directed edge (x, y) if computing an opt sol to subproblem x <u>directly</u> requires knowing an opt sol to subproblem y

Running time: Sum of times needed to solve each subproblem

Time to compute a subproblem is typically linear in the out-degree of its vertex



DP Solution

Arrange to solve each subproblem just once by saving solution in a table

Pick solution from table when revisiting solved subproblems Turns exponential-time solution to a polynomial-time solution

Two basic approaches:

Top-down with memoization

Bottom-up

Top-Down with Memoization

Memorize what has been computed previously Store solution to subproblem of length i in an array entry r[i]

```
MEMOIZED-CUT-ROD(p, n)
 let r[0:n] be a new array // will remember solution values in r
 for i = 0 to n
     r[i] = -\infty
 return MEMOIZED-CUT-ROD-AUX(p, n, r)
MEMOIZED-CUT-ROD-AUX (p, n, r)
 if r[n] \geq 0
                      // already have a solution for length n?
     return r[n]
 if n == 0
     q = 0
 else q = -\infty
     for i = 1 to n // i is the position of the first cut
          q = \max\{q, p[i] + \text{MEMOIZED-CUT-ROD-AUX}(p, n - i, r)\}
                      // remember the solution value for length n
 r[n] = q
 return q
```

Bottom-Up

Sort the subproblems by size and solve the smaller ones first

```
BOTTOM-UP-CUT-ROD(p,n)

let r[0:n] be a new array // will remember solution values in r

r[0] = 0

for j = 1 to n // for increasing rod length j

q = -\infty

for i = 1 to j // i is the position of the first cut

q = \max\{q, p[i] + r[j-i]\}

r[j] = q // remember the solution value for length j

return r[n]
```

How to Reconstruct a Solution?

Extend bottom-up approach to output opt values AND opt choices Save opt choices in a separate table and print it

```
EXTENDED-BOTTOM-UP-CUT-ROD(p, n)
 let r[0:n] and s[1:n] be new arrays
 r[0] = 0
 for j = 1 to n
                            // for increasing rod length j
     q = -\infty
     for i = 1 to j // i is the position of the first cut
         if q < p[i] + r[j-i]
             q = p[i] + r[j - i]
             s[j] = i // best cut location so far for length j
               /\!\!/ remember the solution value for length j
     r[j] = q
 return r and s
 PRINT-CUT-ROD-SOLUTION (p, n)
  (r, s) = \text{EXTENDED-BOTTOM-UP-CUT-ROD}(p, n)
  while n > 0
      print s[n] // cut location for length n
      n = n - s[n] // length of the remainder of the rod
```

Example of Output

Example: PRINT-CUT-ROD-SOLUTION(p, 8)

length i	1	2	3	4	5	6	7	8
price p_i	1	5	8	9	10	17	17	20

Example of Output

Example: PRINT-CUT-ROD-SOLUTION(p, 8)

length i	1	2	3	4	5	6	7	8
price p_i	1	5	8	9	10	17	17	20

i									
r[i]	0	1	5	8	10	13	17	18	22
s[i]		1	2	3	2	2	6	1	2

Runtime and Space Complexity

Top-down: To solve a subproblem of size n, the for loop iterates n times → total #iters form an arithmetic series

Bottom-up: #Iters of inner for loop forms an arithmetic series

Running time: $\theta(n^2)$

Space complexity: $\theta(n)$

Chain of Thought

- What are my subproblems?
- What are the decisions to solve each subproblem?
- Recursive formulation
 - Base case
- How many subproblems? What is the running time per subproblem?
- What is the overall running time?

P6: Knapsack w/ Repetition

Given a "knapsack" that can hold a maximum weight of W pounds, a robber has n items to pick from. Each item has weight $\{w_1, w_2, ..., w_n\}$ and dollar value $\{v_1, v_2, ..., v_n\}$.

What's the *most valuable* combination of items the robber can fit into his bag / knapsack?

Generalizes to a wide variety of resource-constrained selection problems!

Example

Item	Weight (lbs)	Value (\$)
1	7	12
2	3	2
3	20	41

$$W = 58 lbs$$

Option 1: $2 \times Item3 + 1 \times Item2 + 2 \times Item1$

Weight: $40 + 3 + 14 = 57 \ lbs \le 58 \ lbs$

Value: 82 + 2 + 24 = \$108

Option 2: $2 \times Item3 + 6 \times Item2 + 0 \times Item1$

Weight: $40 + 18 + 0 = 58 lbs \le 58 lbs$

Value: 82 + 12 + 0 = \$94

A Brute-Force Approach

- Try all possible combinations of items
- Compute weight and profits; eliminate combinations with total weight > W
- Find max value

Runtime: $\sum_{k=0}^{n} C(n, k) = \Omega(2^{n})$

DP: Structure of an optimal solution

Idea: Look at smaller knapsack capacities $w \le W$

Let K(w) be the max value achievable with a knapsack capacity $w \le W$.

We want K(W).

If the optimal solution includes item i,

- removing this item leaves an optimal solution to $K(w w_i)$
- Add value of item i, which is v_i

Need to consider all possible values of *i*

DP: A Recursive Solution

$$K(w) = \max\{K(w - w_i) + v_i\} \,\forall i \colon w_i \le w$$

Base case: K(0) = 0

DP: Pseudocode (Tabular, bottom-up)

$$K(0)=0$$
 for $w=1$ to W :
$$K(w)=\max\{K(w-w_i)+v_i:w_i\leq w\}$$
 return $K(W)$

O(W) subproblems Each entry can take up to O(n) time to compute Runtime: O(nW)

If $W \sim 2^8 or \ 2^{20}$, i.e., 8bits to 20bits, complexity increases exponentially with #bits

P7: Knapsack w/o Repetition

If repetitions are not allowed to our knapsack problem. How can we solve it using DP?

 $K(j, w) = \max \text{ value achievable using knapsack of capacity } w \text{ and items } 1, \dots, j$

We need K(n, W)

$$K(j, w) = \max\{K(j-1, w-w_j) + v_j, K(j-1, w)\}$$

P5: Example

Item	1	2	3	4	5
W (lbs)	1	2	1	3	5
V (\$)	10	40	20	20	60

$$W = 10 lbs$$

```
\begin{aligned} & \text{j} = 1, \, \text{w} = 1, \, w_j = 1, \, v_j = 10 \\ & \text{K}[1, \, 1] = \max(\text{K}[0, 0] + 10, \, \text{K}[0, 1]) = 10 \\ & \text{K}[1, \text{w}] = \max(\text{K}[0, \, \text{w} - w_1] + 10, \, \text{K}[0, \text{w}]); \, \text{K}[0, \, \text{w}] = 0; \, \text{K}[0, \, \text{w} - w_1] = 0 \,\, \forall 2 \leq w \leq 10 \\ & \text{j} = 2, \, \text{w} = 1, \, w_j = 2, \, v_i = 40; \, w_j > w, \, \text{so} \,\, \text{K}[2, 1] = \text{K}[1, 1] \\ & \text{j} = 2, \, \text{w} = 2, \, w_j = 2, \, v_i = 40; \, w_j \leq w, \, \text{so} \,\, \text{K}[2, 2] = \max(\text{K}[1, 0] + 40, \, \text{K}[1, 2]) = \max(40, 10) = 40 \\ & \text{j} = 2, \, \text{w} = 3, \, w_j = 2, \, v_i = 40; \, w_j \leq w, \, \text{so} \,\, \text{K}[2, 3] = \max(\text{K}[1, 1] + 40, \, \text{K}[1, 3]) = \max(10 + 40, 10) = 50 \\ & \text{K}[2, \text{w}] = \max(\text{K}[1, \, \text{w} - w_2] + 40, \, \text{K}[1, \text{w}]) = 50 \end{aligned}
```

	weight capacity \rightarrow		0	1	2	3	4	5	6	7	8	9	10
weights	values	0	0	0	0	0	0	0	0	0	0	0	0
1	10	1	0	10	10	10	10	10	10	10	10	10	10
2	40	2	0	10	40	50	50	50	50	50	50	50	50
1	20	3	0	20	40	60	70	70	70	70	70	70	70
3	20	4	0	20	40	60	70	70	80	90	90	90	90
5	60	5	0	20	40	60	70	70	80	100	120	130	130

K[n,W] = K[5,10] = 130= max knapsack value

P8: Weighted Interval Scheduling

Given a set of n jobs, each job $j \in n$ starts at s_j and finishes at f_j and has a weight or value v_j . Two jobs are compatible if they don't overlap.

Goal: Find maximum weight subset of mutually compatible jobs

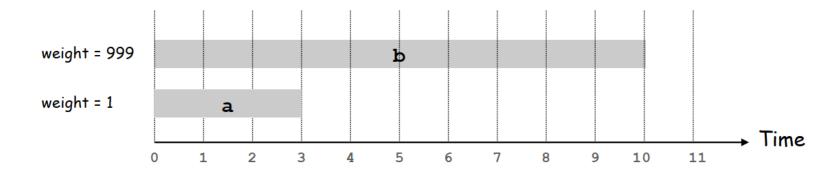
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When does greedy work? $v_j = 1, \forall j = 1, 2, ..., n$

-- When all weights are 1 (or, the same)



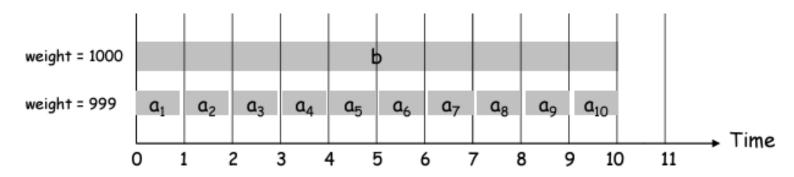
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When does greedy work? $v_i = 1, \forall j = 1, 2, ..., n$

- When all weights are 1 (or, the same)
- Sort by weight?



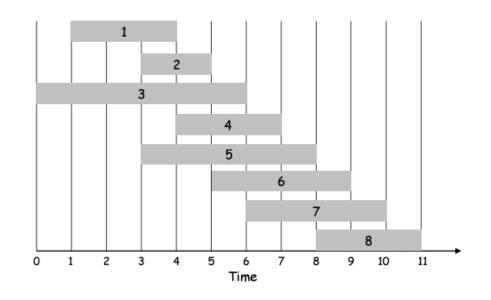
Preprocessing Step (Something new!)

<u>Idea:</u>

Sort by finish times: $f_1 \le f_2 \le \cdots \le f_n$.

Maintain a table p(j) = i, where i is the largest index i < j s.t. job i and j are m.c.

Ex: p(8) = 5, p(7) = 3, p(2) = 0.



j	p(j)
0	1
1	0
2	0
3	0
4	_
5	0
6	2
7	3
8	5

DP Approach

Subproblems: WIS(j) = max weight subset of jobs start at 1 and ending at j

Decisions:

- Include j: add profit v_j , include optimal solution to previous set of m.c. jobs, i.e., 1, ..., p(j)
- Do not include j: include optimal solution to previous jobs, 1, ..., j-1

$$WIS(j) = \begin{cases} 0, & if j = 0 \\ \max\{v_j + WIS(p(j)), WIS(j-1)\}, otherwise \end{cases}$$

Running time:

 $O(n \log n)$ to sort. O(n) to compute $WIS(j) \forall j = 1, ..., n$

P9: Share Trading

We're given the price of a stock over n consecutive days i = 1, 2, ..., n. For each day i, we're given a price p(i) per share for the stock on that day. (Assume that the price is fixed per day.)

How should we choose a day i on which to buy the stock and a later day j > i on which to sell it so that we maximize the profit per share, p(j) - p(i)? If there is no way to make money during the n days, we should conclude this instead.

Share Trading

Subproblem: Let OPT(j) $(j = 1, ..., n) = \max$ possible return if investor sells share on day j.. We want OPT(n)

Decisions: On day j, investor either holding it on day j-1 or weren't.

- If not, OPT(j) = 0.
- If yes, then OPT(j) = OPT(j-1) + (p(j) p(j-1)).

Recursion:

$$OPT_j = \max\{OPT(j) + (p(j) - p(j-1)), 0\}$$

Base case: OPT(1) = 0

Running time: O(n) subproblems, O(1) per subproblem, so O(n)

Problems So Far ...

Prob #	Definition	Opt Type	Template	Running Time (only DP part)
1	Shortest paths in DAGs	Min	#1	$O(V + E) \times O(1)$
2	Bellman Ford	Min	#1	$O(V) \times O(E)$
3	Floyd Warshall	Min	#2	$O(n^2) \times O(n)$
4	Transitive Closure of Graph	Min	#2	$O(n^2) \times O(n)$
5	Rod Cutting	Max	#1	$O(n) \times O(n)$
6	Knapsack w/ repetition	Max	#1	$O(W) \times O(n)$
7	Knapsack w/o repetition	Max	#1	$O(W) \times O(n)$
8	Weighted Interval Scheduling	Max	#1	O(n) x O(1)
9	Share trading	Max	#1	O(n) x O(1)

Lecture 12 summary

Rod cutting

Knapsack w/ repetition

Knapsack w/ repetition

Weighted Interval Scheduling

Share trading