

Rod Cutting

2D DP

`http://www.cs.unh.edu/~ruml/cs758`

Rod Cutting

- The Problem
- Optimal Value
- An Algorithm
- Solution Recovery
- Properties
- Substructure
- Break

2D DP

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The Problem

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■ The Problem

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Given table of profits p_i for each possible integer length i , find the best way to cut a rod of length n . Cuts are free, but must be of integer length.

length i	1	2	3	4	5	6	7	8	9	10
profit p_i	1	5	8	9	10	17	17	20	24	30

$\approx 2^{n-1}$ possible solutions! How to solve in $O(n^2)$ time?

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2D DP

Step 1: write down value of optimal solution

$best(n)$ = best profit achievable for length n

$best(n) = \max_{first=1}^n (p_{first} + best(n - first))$

$best(0) = 0$

What is the complexity of the naive recursive algorithm?

How to make this efficient?

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Step 2: compute optimal value (top-down or bottom-up)

1. $\text{best}[0] \leftarrow 0$
2. for len from 1 to n
3. $\text{best}[\text{len}] \leftarrow \max_{\text{first}=1}^{\text{len}} (p_{\text{first}} + \text{best}[\text{len} - \text{first}])$
4. $\text{best}[n]$

Will this access uninitialized data?

What is the complexity?

Solution Recovery

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2D DP

```
1. best[0] ← 0
2. cut[0] ← 0
3. for len from 1 to n
4.     best[len] ←  $-\infty$ 
5.     for first from 1 to len
6.         this ←  $p_{\text{first}} + \text{best}[\text{len} - \text{first}]$ 
7.         if this > best[len]
8.             best[len] ← this
9.             cut[len] ← first
10. print best[n]
11. while n > 0
12.     print cut[n]
13.     n ← n - cut[n]
```

Properties

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2D DP

- optimal substructure: global optimum uses optimal solutions of subproblems
- ordering over subproblems: solve 'smallest' first, build 'larger' from them
- 'overlapping' subproblems: polynomial number of subproblems, each possibly used multiple times
- independent subproblems: optimal solution of one subproblem doesn't affect optimality of another

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shortest path

- path to any intermediate vertex along optimal path must be optimal path to that vertex. otherwise, could be shorter.

longest simple path

- path to an intermediate vertex along optimal path may not use vertices used elsewhere: subproblems are not independent.

Break

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■ Break

2D DP

■ asst 4

■ asst 5

- LCS
- Recursive
- Substructure
- DP Summary
- EOLQs

Two-Dimensional Dynamic Programming

Longest Common Subsequence

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2D DP

■ LCS

■ Recursive

■ Substructure

■ DP Summary

■ EOLQs

Given two strings, x of length m and y of length n , find a common (non-contiguous) subsequence that is as long as possible.

$x = \text{ABCBDAB}$

$y = \text{BDCABA}$

Longest Common Subsequence

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2D DP

■ LCS

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■ Substructure

■ DP Summary

■ EOLQs

Given two strings, x of length m and y of length n , find a common (non-contiguous) subsequence that is as long as possible.

$x = \text{ABCB DAB}$

$y = \text{BDCABA}$

$\text{LCS} = \text{BCBA or BCAB}$

$x' = \text{AB-C-BDAB}$

$y' = \text{-BDCAB-A-}$

What is the complexity of the naive algorithm?

How to make this efficient?

Recursive Approach

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2D DP

■ LCS

■ Recursive

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$LCS(i, j)$ means length of LCS considering only up to x_i and y_j

Recursive Approach

Rod Cutting

2D DP

■ LCS

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■ DP Summary

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$LCS(i, j)$ means length of LCS considering only up to x_i and y_j

$$LCS(i, j) = \begin{cases} 0 & \text{if } i \text{ or } j = 0 \\ LCS(i - 1, j - 1) + 1 & \text{if } x_i = y_j \\ \max(LCS(i - 1, j), \\ \quad LCS(i, j - 1)) & \text{otherwise} \end{cases}$$

global optimum uses optimal solutions of subproblems

Proof by contradiction: What if subsolution were not optimal?

Let z be an $LCS(i, j)$ of length k .

1. If $x_i = y_j$, then $z_k = x_i = y_j$ and $LCS(i - 1, j - 1) = z_0..z_{k-1}$.
Not including z_k makes LCS suboptimal: contradiction!
If $z_0..z_{k-1}$ were not LCS, z could be longer, hence not optimal: contradiction!
2. If $x_i \neq y_j$ and $z_k \neq x_i$, then z is $LCS(i - 1, j)$.
If longer exists, z would not be an LCS: contradiction!
3. If $x_i \neq y_j$ and $z_k \neq y_j$, then z is $LCS(i, j - 1)$
Similar to 2.

Summary of Dynamic Programming

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■ LCS

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■ EOLQs

1. optimal substructure: global optimum uses optimal solutions of subproblems
 2. ordering over subproblems: solve 'smallest' first, build 'larger' from them
 3. 'overlapping' subproblems: polynomial number of subproblems, each possibly used multiple times
 4. independent subproblems: optimal solution of one subproblem doesn't affect optimality of another
- top-down: memoization
 - bottom-up: compute table, then recover solution

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For example:

- What's still confusing?
- What question didn't you get to ask today?
- What would you like to hear more about?

Please write down your most pressing question about algorithms and put it in the box on your way out.

Thanks!