Dynamic Programming

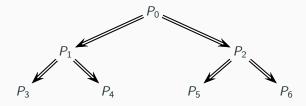
Advanced Algorithms and Data Structures - Lecture 5

Venanzio Capretta

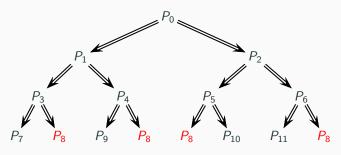
Thursday 29 October 2020

School of Computer Science, University of Nottingham

• Divide-and-Conquer: Split the problem into smaller subproblems - solve them recursively



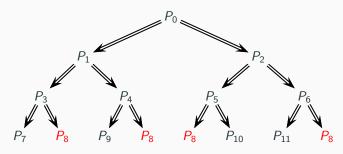
Divide-and-Conquer:
 Split the problem into smaller subproblems - solve them recursively



We may hit the same subproblem in different branches

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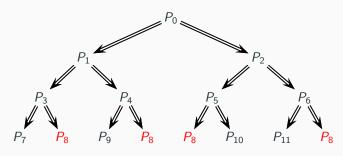
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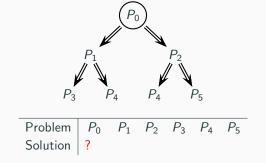


- We may hit the same subproblem in different branches
- ullet Divide-and-Conquer would recompute P_8 four times
- Dynamic programming:
 Remember the solution of P₈ after the first time

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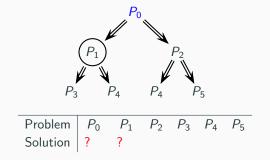
Dynamic Programming idea:

- Keep a table of already computed subproblems
- Look up a subproblem in the table before recomputing
- New subproblem? Compute the solution and add it to the table



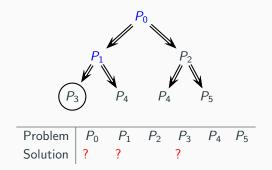
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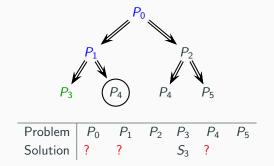
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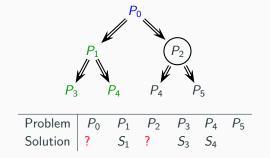
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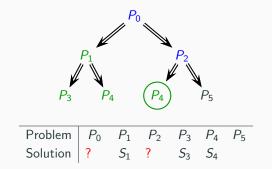
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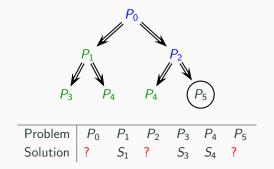
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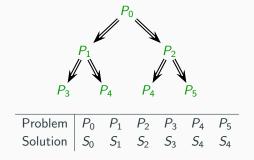
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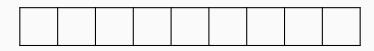


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Cut a rod into pieces maximizing their total price

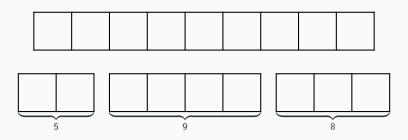


Cut a rod into pieces maximizing their total price
We have a table of prices for pieces of different length
You must cut the rod to maximize the total price of the pieces

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length	1	2	3	4	5	6	7	8	9	10
price	1	5	8	9	10	17	17	20	24	30

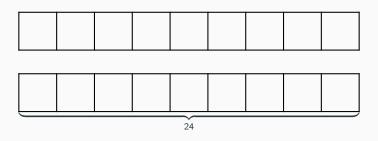
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If we split it in 9 = 2 + 4 + 3, price: 5 + 9 + 8 = 22

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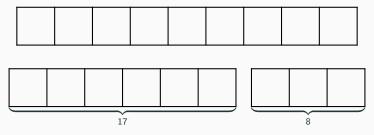
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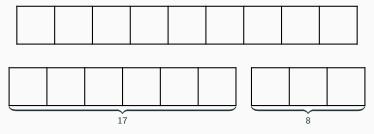
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If we split it in 9 = 6 + 3, price: 17 + 8 = 25

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If we split it in 9 = 2 + 4 + 3, price: 5 + 9 + 8 = 22

If we don't split it, price: 24

If we split it in 9 = 6 + 3, price: 17 + 8 = 25 (maximum)

length	1	2	3	4	5	6	7	8	9	10
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Optimal Cut Equations (1)

We can adopt a divide-and-conquer strategy:

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Equations expressing the price r_n of an optimal cut of a rod of length n:

$$r_1 = p_1$$

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

We cut the rod of length n into two rods of length i and n-i in all possible ways (explicitley consider the uncut price p_n)

Optimal Cut Equations (2)

We can improve the algorithm by taking the first cut to be definitive:

The first half will not be further cut,

so we don't need a recursive call for it:

$$r_0 = 0$$

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

This takes care also of

- r_1 (it automatically gives p_1)
- the uncut option when i = n

Observation:

Possible improvement: assume that the first cut is the largest:

Cutting 9 = 3 + 6 is equivalent to 9 = 6 + 3

Order of cuts is unimportant: only consider the second one

But we don't follow this path (exercise: try)

We'll look at a better algorithm using Dynamic Programming

```
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Exercise: Modify it so it returns the cuts (the list of ks)

Complexity of Naive Algorithm

The Complexity is Exponential: $T(n) = O(2^n)$

(See IA for the formal derivation)

Problem:

We recompute several times optimal cuts for the same length Eg when computing maxCut pr 9, among the possibilities we have 9=5+4, 9=3+2+4, 9=4+1+4 etc

The optimal solution for a rod of length 4 is recomputed each time.

Idea: keep a table with the optimal prices already computed and look up in it before recomputing.

DP Solution: Imperative

We construct a global array/table bestCut that cointains the optimal cut for every length: bestCut!!i = total price of optimal cut for a rod of length i

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- Bottom-Up Method: Systematically compute all the values in the table in order: bestCut!!0, bestCut!!1, ..., bestCut!!n; when computing bestCut!!i, we already know all the previous values are in the table

Bottom-Up is efficient if we know in advance that we need to compute all the values in the table

DP and lazy evaluation

In Functional Programming:

- Declarative Style: We can just define the table of values, without worrying about the order in which it is computed and when values will be available
- Lazy Evaluation: Entries of the table will be computed when needed and they persist for further calls

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Optimal Substructure

The optimal solution to an instance of the problem (eg cutting a rod of length n) contains optimal solutions of some subproblems (cutting rods of shorter length)

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 - The optimal solution to an instance of the problem (eg cutting a rod of length n) contains optimal solutions of some subproblems (cutting rods of shorter length)
- Overlapping Subproblems Different branches of the computation of an optimal solution require to compute the same subproblem several times