## Week 11 – S01 Dynamic Programming contd.

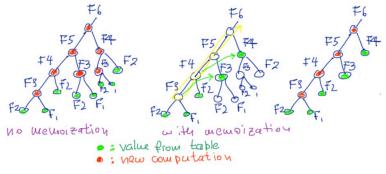
50.004 Introduction to Algorithms

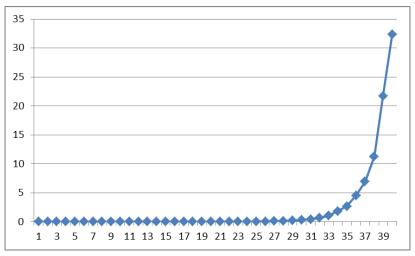
Dr. Subhajit Datta

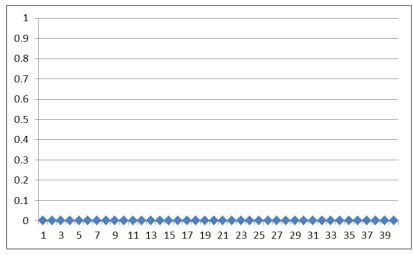
ISTD, SUTD

#### Memoization

 Store values of sub-problems in table, to avoid computing them twice



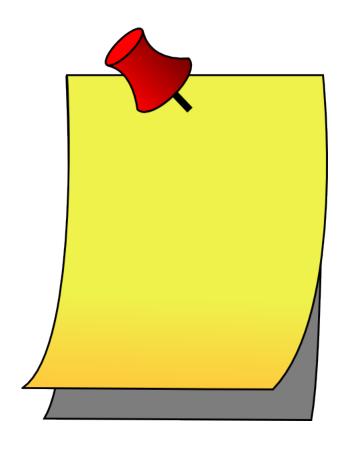




Complexity:  $\Theta(2^n)$ 

Complexity:  $\Theta(n)$ 

#### DP: Memoization not memorization





#### Fibonacci numbers

$$F_1 = F_2 = 1$$
,  $F_n = F_{n-1} + F_{n-2}$ 

Naïve algorithm

fib(n):

if  $n \le 2$ : f = 1else f = fib(n-1) + fib(n-2)return f Memoized DP algorithm

```
memo = {}

fib(n):

if n in memo: return memo[n]

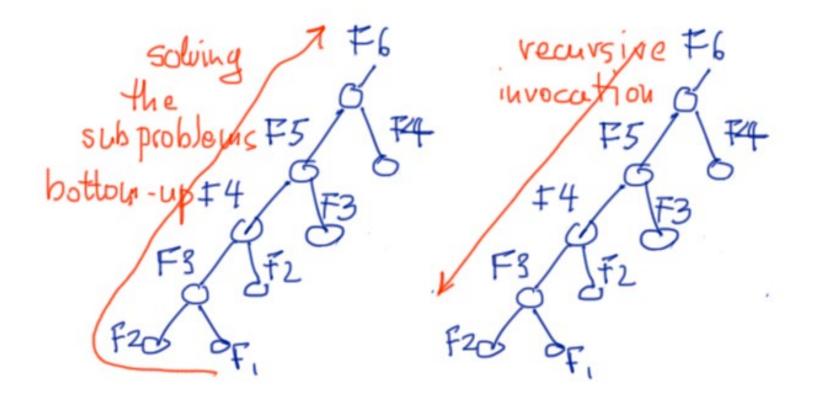
if n \le 2: f = 1

else f = \text{fib}(n-1) + \text{fib}(n-2)

memo[n] = f

return f
```

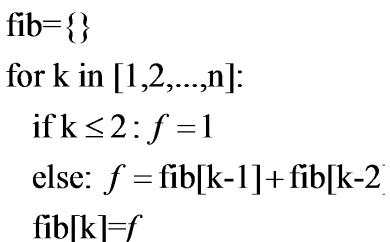
#### Top-down versus bottom-up

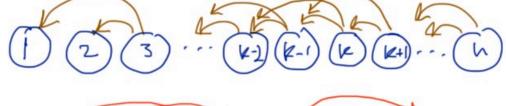


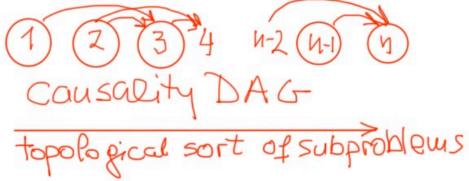
Bottom-up method: Solve sub-problems in a "causal" sequence from smaller to larger

#### Bottom-up DP algorithm

```
Sub-problem dependency graph
```







- Exactly the same computation as memoized DP (recursion rolled back)
- In general: topological sort of sub-problem dependency graph => needs DAG structure!!
- What are the benefits?

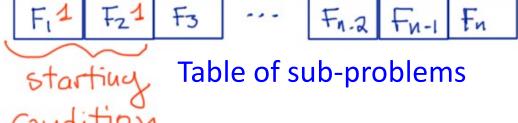
return fib[n]

- Practically faster (no recursion)
- Can save space (just remember last 2 values) => Θ(1) space

### Bottom up: filling-in a table

Fill-in the table of sub-problems

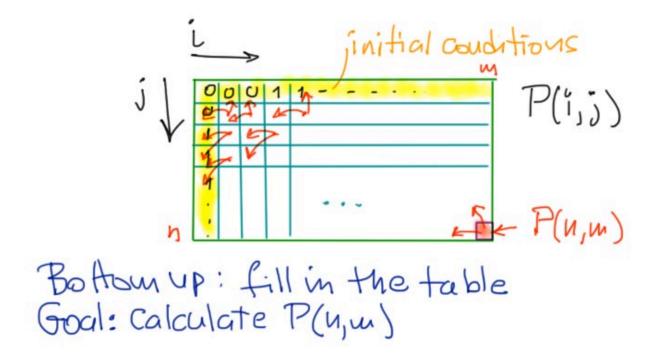




Note: There should be no circular dependency between sub-problems

### Bottom up: filling-in a table

Example with 2 dimensions sub-problem is P(i, j), hence 2-d table



Note: There should be no circular dependency between sub-problems

#### Fibonacci: Bottom-up (Iterative)

```
table = {}
def fiboBottomUp(n):
    for i in range(1,n+1):
        if i <= 2:
            fibo = 1
        else:
            fibo = table[i-1]+table[i-2]
        table[i] = fibo
    return table[n]</pre>
```

### Dynamic programming: Steps

- 1. Define sub-problems
- 2. Guess (part of the solution)
- 3. Relate sub-problem solutions
- 4. Recurse plus memoize
  - Or, Build table bottom up (if there are no circular dependencies)
- 5. Solve original problem by combining subproblem solutions

#### Elements of dynamic programming

#### **Optimal substructure**

The solution to a problem can be obtained by solutions to sub-problems with no circular dependency

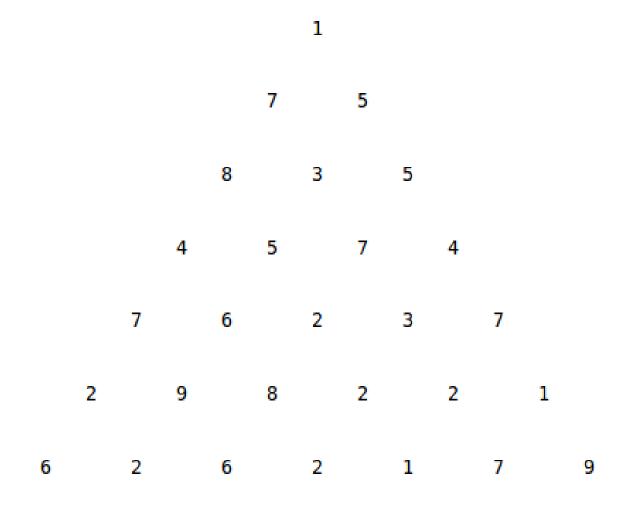
#### **Overlapping sub-problems**

A recursive solution contains a "small" number of distinct sub-problems (repeated many times)

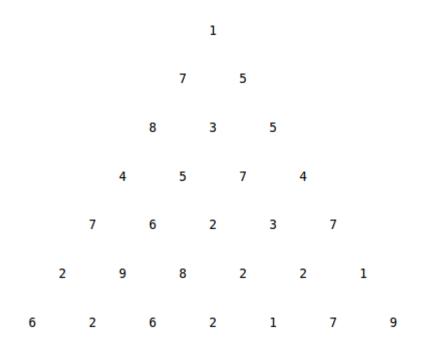
DP relies on sub-problems being independent and overlapping: A contradiction?

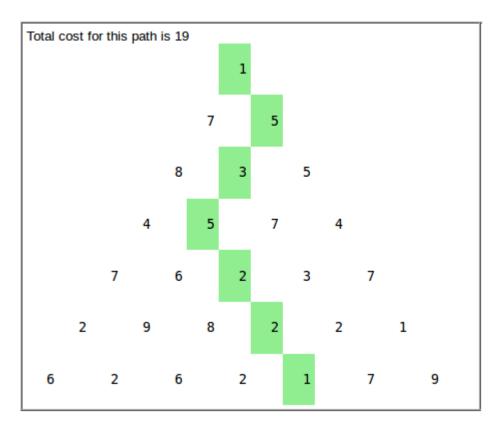
- Two sub-problems of the same problem are independent if they do not share resources
- Two sub-problems are overlapping if they are really the same sub-problem that occurs as a subproblem of different problems
- So, this is not a contradiction!

## Example

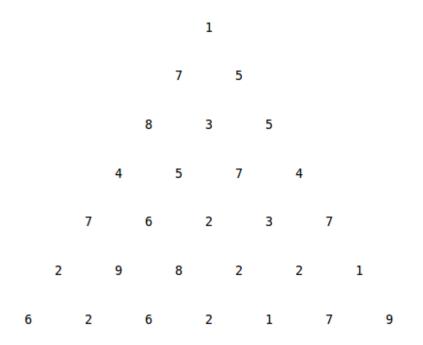


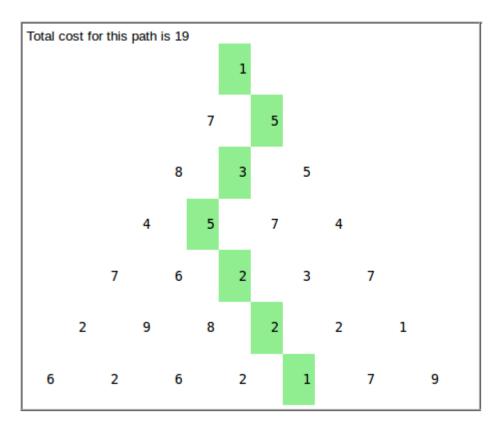
#### One path connecting top to bottom



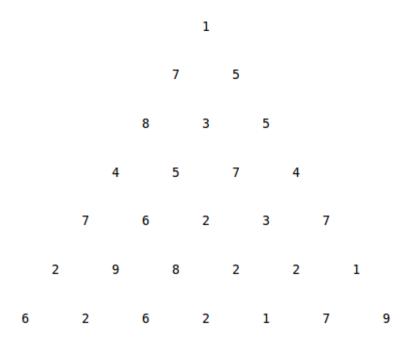


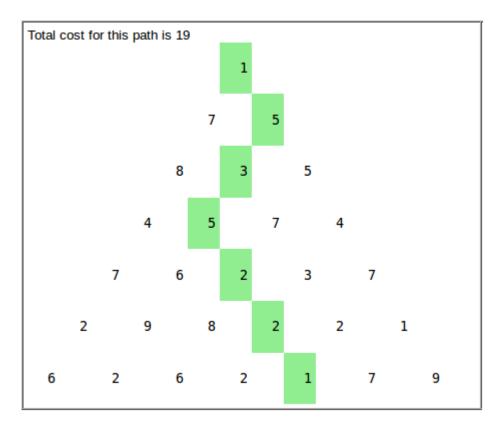
### What is this approach called?



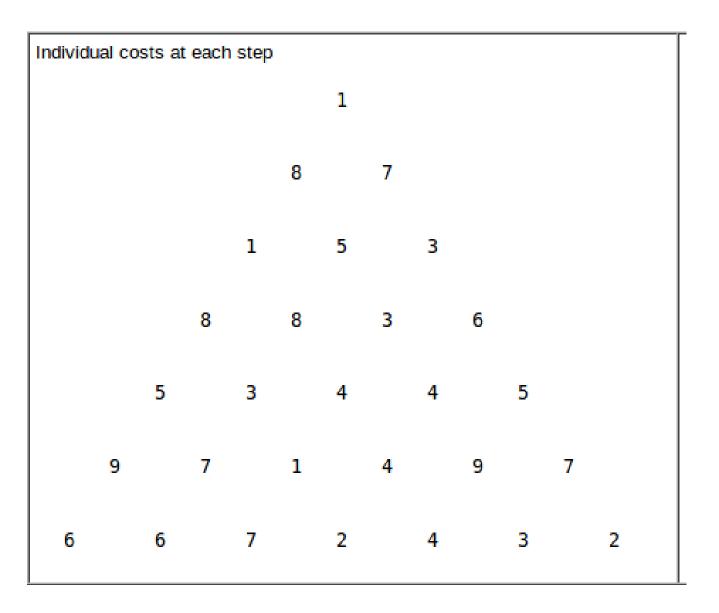


## Greedy approach!





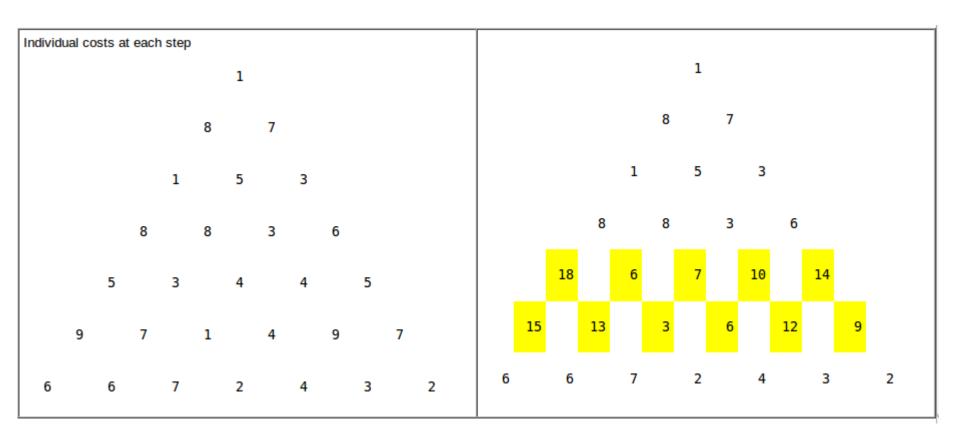
#### Find the path from top to the bottom with the least cost



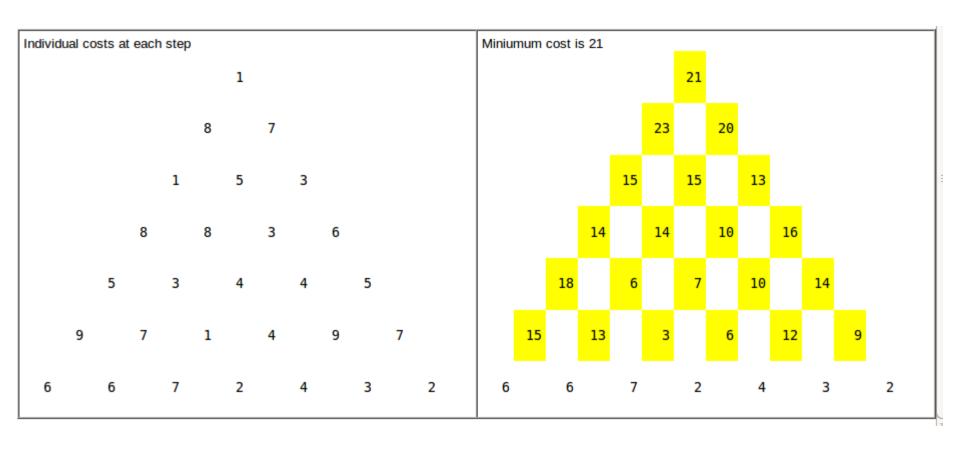
## Solution steps



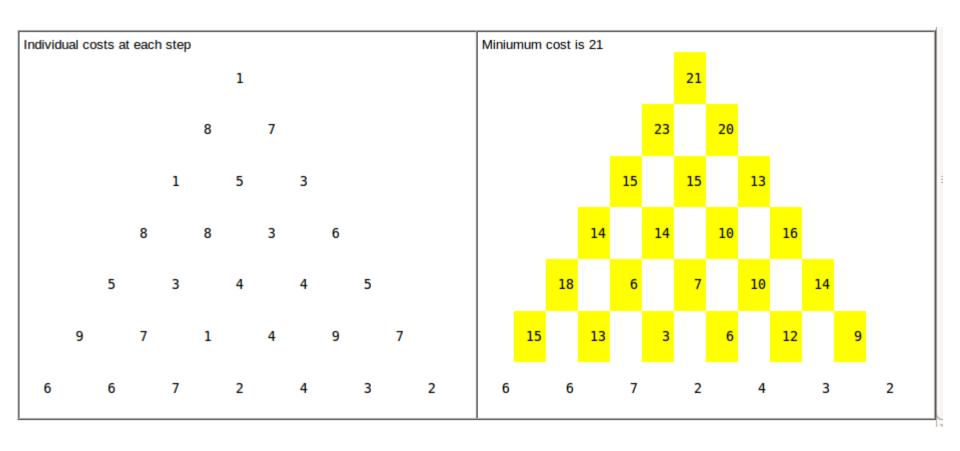
## Solution steps



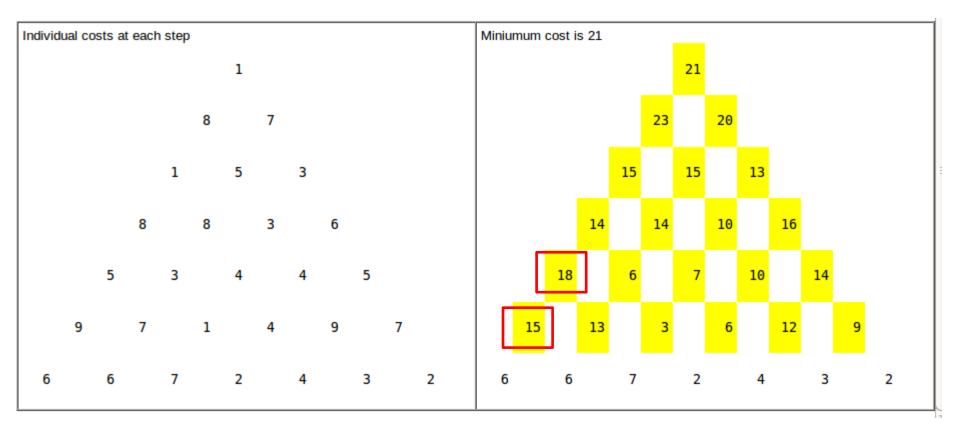
#### Solution



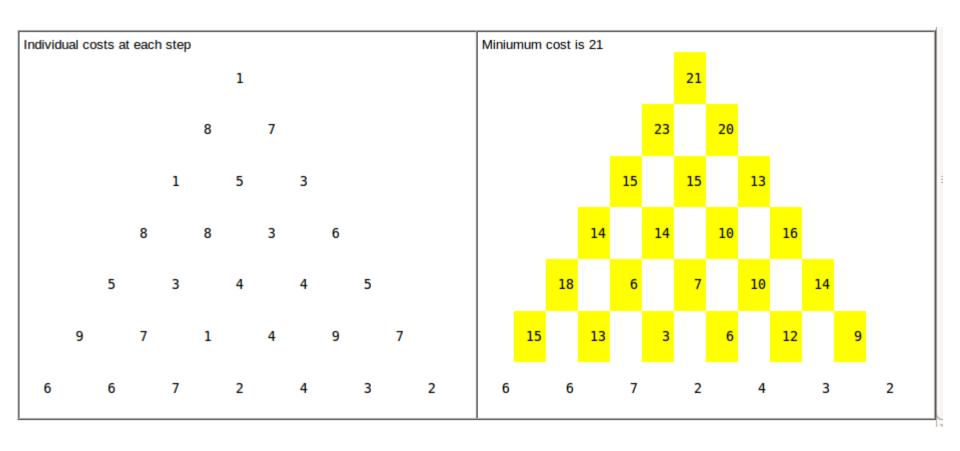
#### Where is dynamic programming here?

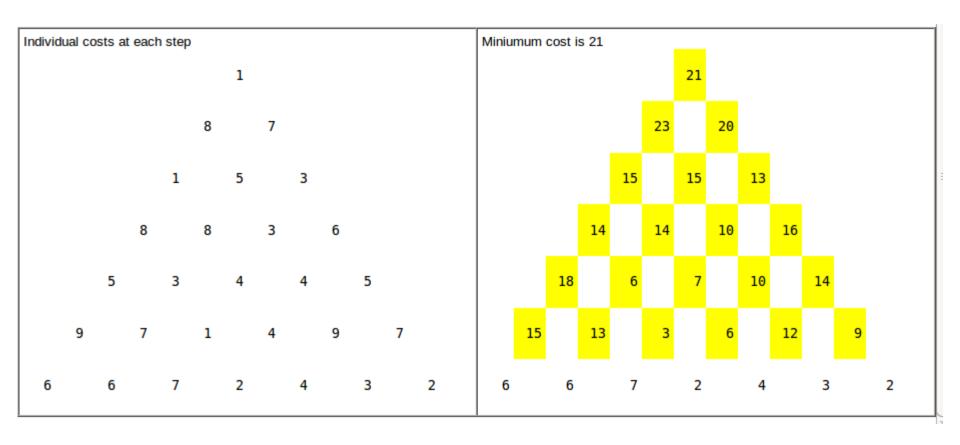


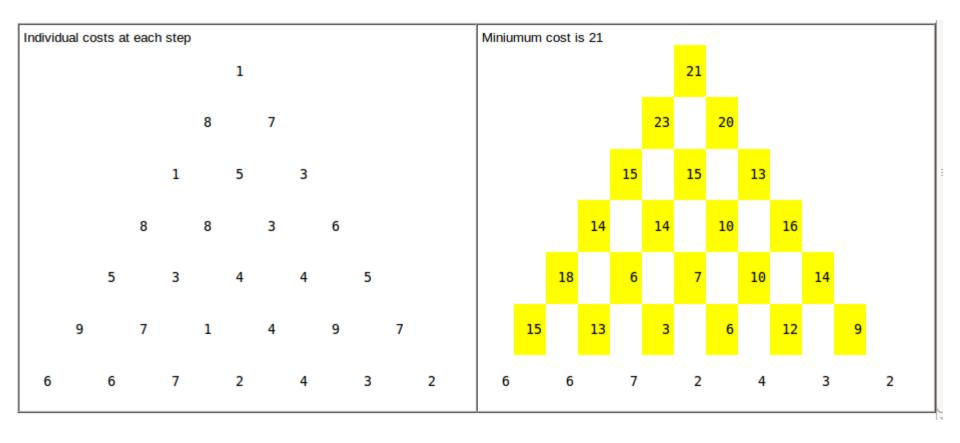
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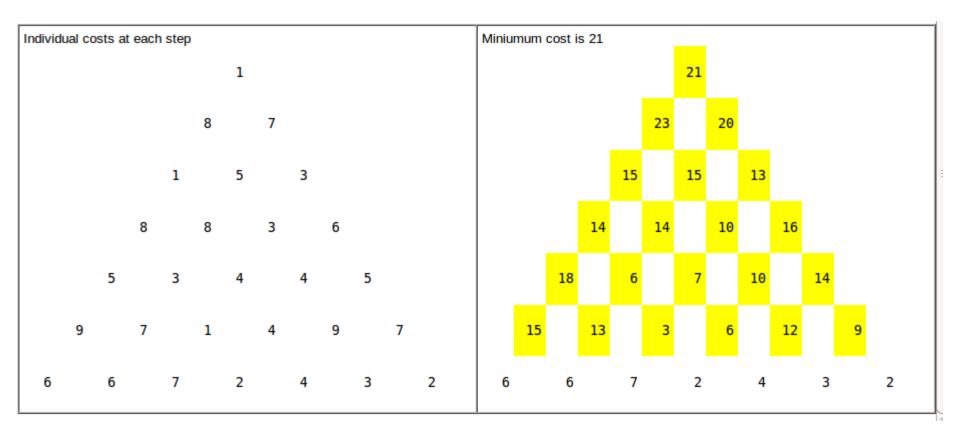


#### What value would a greedy approach give?

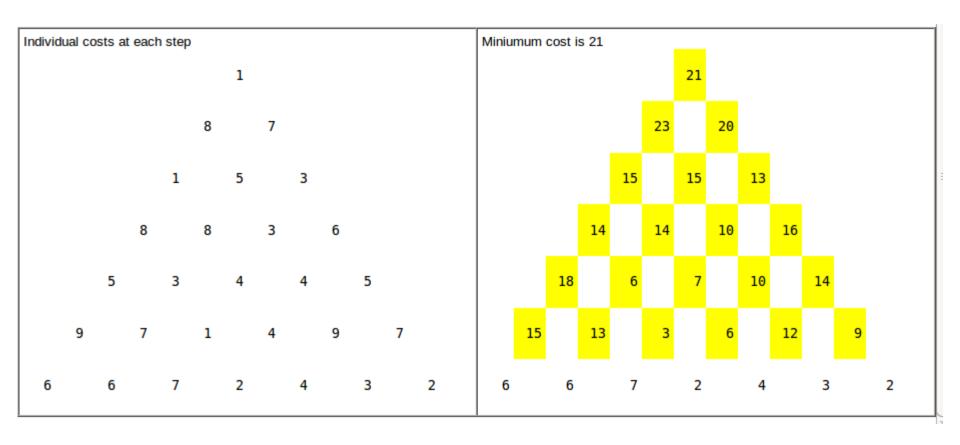




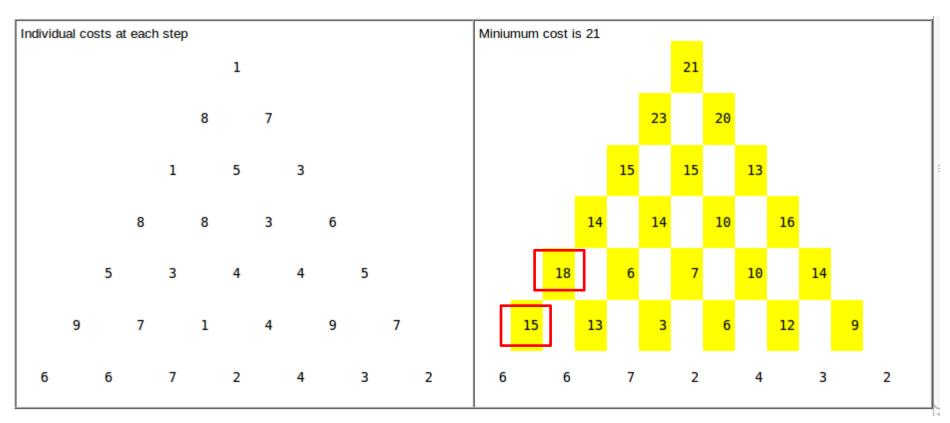




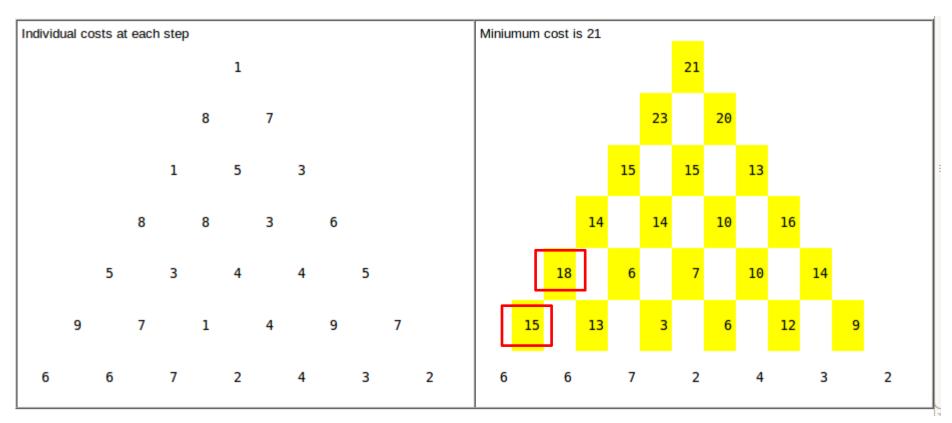
1->7->3->3->4->1->2 => 21, or 1->7->3->3->4->4->2 => 24 So, better be DP than greedy 
$$\odot$$



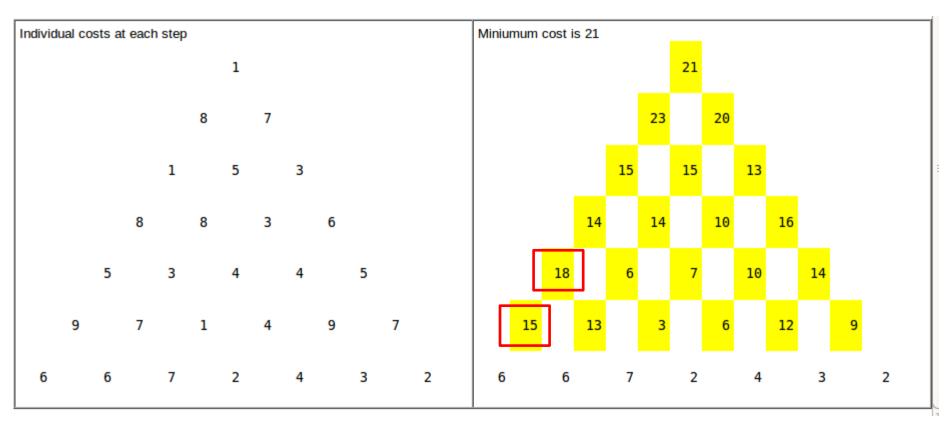
# Write down the DP steps you followed in the form of an algorithm



# Think about how the DP algorithm can be coded into a computer program



## Check whether your program returns the correct result



## How do we use dynamic programming to solve some problem P?

- Break-down P using divide-and-conquer into sub-problems (SPs)
  - By writing the solution of P in terms of the solutions of subproblems of P
  - Recurse and memoize OR build SP table bottom up
  - Complexity: we assume that due to memoization, each subproblem is solved only once

#### Alternative way to think about it

- How do we use dynamic programming to solve some problem P?
- Break-down P using divide-and-conquer into sub-problems
  - Define potential sub-problems
  - Guess: a possible solution in terms of solutions of sub-problems
  - Optimization: optimize over all possible guesses, k= # of guesses
  - Recurse and memoize OR build table bottom up
  - Complexity: # of potential sub-problems that need to be solved x k guesses/sub-problem (due to memoization each sub-problem is solved only once; each guess takes Θ(1) time)

- A rod of size n
- A table of prices  $p_i$  = price in the market of a rod of size i = 1, 2, ..., n
- Determine the maximum revenue DP[n] obtained by cutting the rode into pieces and selling these to the market

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

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Do we need to consider all possible combinations?

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Do we need to consider all possible combinations? No! use DP!

size of piece	1	2	3	4
market price	2	5	7	8

- Rod of size n=4
- Write down the DP equations (recurrence)
- Which are my sub-problems?
- How are these related?

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- Rod of size n=4
- Write down the DP equations (recurrence)
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$$DP[j] = \max \text{ revenue obtained from}$$
a rod of size  $j$  a guess
$$= p_k + DP[j-k] \text{ for some } k \Rightarrow DP[j] = \max_{i=0,1,...,j} \{p_i + DP[j-i]\}$$

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- Rod of size n=4
- Write down the DP equations (recurrence)
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- How are these related?
   DP[k] = maximum value i can get from a rod of size k

$$DP[k] = \max_{i} \{p_i + DP[k-i]\}, 1 \le i \le k$$
  
 $DP[0] = 0$ 



*DP*[0] *DP*[1] *DP*[2] *DP*[3] *DP*[4]

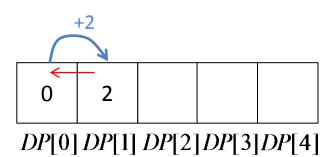
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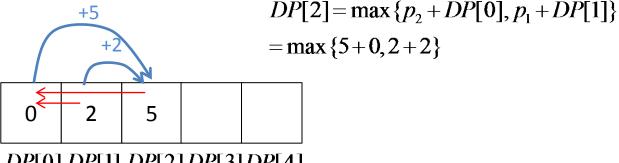
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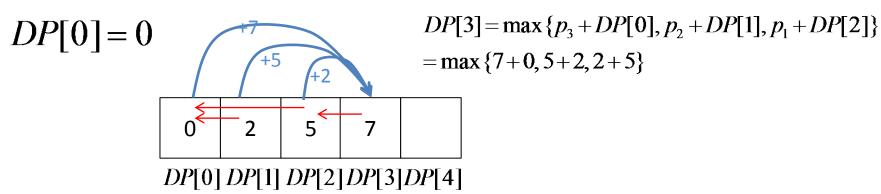
DP[0] DP[1] DP[2] DP[3] DP[4]

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DP[k] = maximum value i can get from a rod of size k

$$DP[k] = \max_{i} \{p_i + DP[k-i]\}, 1 \le i \le k$$

DP[0] = 00 2 5 7 10

DP[0] DP[1] DP[2] DP[3] DP[4]

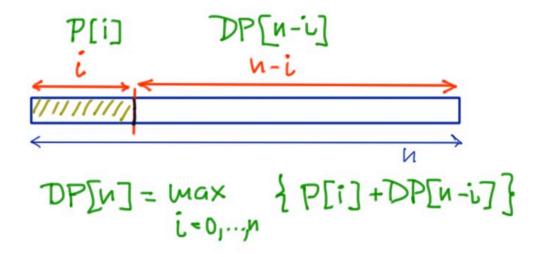
$$DP[4] = \max\{p_4 + DP[0], p_3 + DP[1], p_2 + DP[2], p_1 + DP[3]\}$$
  
= \max\{8 + 0, 7 + 2, 5 + 5, 2 + 7\}

General DP formulation:

 $DP[j] = \max \text{ revenue obtained from a rod of size } j$ 

$$= p[k] + DP[j-k]$$
 for some  $k \Rightarrow$ 

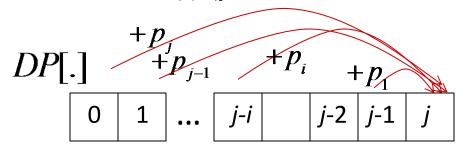
$$DP[j] = \max_{i=0,1,...,j} \{p[i] + DP[j-i]\} \quad \text{-----} \quad j \text{ possible guesses}$$



```
r[i]=DP[i], S[i]=size of Piece to be taken out from rad i
EXTENDED-BOTTOM-UP-CUT-ROD(p, n)
   let r[0..n] and s[0..n] be new arrays
   r[0] = 0
   for j = 1 to n \neq solve all sub-problems
       q=-\infty
          for i = 1 to j
6
   return r and s
10
```

### Lets fill the table (bottom-up solution of DP)

$$DP[j] = \max_{i=0,1,...,j} \{p_i + DP[j-i]\}$$



Topological sort: compute *DP*[*j*] from left to right

$$s[j] = \underset{i=0,1,...,j}{\operatorname{arg\,max}} \{ p_i + DP[j-i] \}$$

Exercise1: fill in the table with the solutions DP[j], j=0,...,10, of the sub-problems, and the optimal decisions s[j] for each j

Exercise2: the complexity is a: n, b: n^2, c: n^3

### **Answer**

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

len	0	1	2	3	4	5	6	7	8	9	10	
DP[]	0	1	5	8	10	13	17	18	22	25	30	
S[]	0	0	0	0	2	2	0	1	2	3	0	

```
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).
```

### The text justification problem

 Split text into "good" lines so that a set of consecutive lines looks "nice"

```
bad! blah blah 0b blah blah 4b good! blah 8b blah blah 4b averylongword 0b averylongword 0b
```

Question 1: Which algorithm is used in the "bad case"?

- a. breaks randomly the text into lines that fit the given page length
- b. works "myopically": fills each line to the maximum possible without caring for the next lines

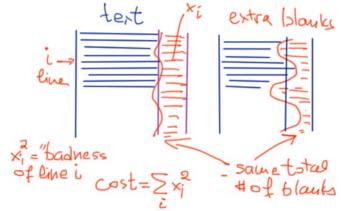
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```
bad! blah blah 0b blah blah 4b good! blah 8b blah blah 4b averylongword 0b averylongword 0b
```

Question 2: Guess a good mathematical criterion for assessing "badness" of a solution

- 1. total # of blank spaces,
- 2. worse case of extra blank spaces in some line,
- 3.  $\sum_{\text{all lines i}} (\text{# of extra blank spaces in line } i)^2$



Why use the cost  $\sum_{\text{all lines}}$  (# of extra blank spaces in line i)<sup>a</sup>, a > 1?

Consider the problem of allocating K extra blank spaces to m lines. If we use the badness function  $\sum_{i=1,\dots,m} x_i^2$ ,  $x_i = \text{extra blanks in line } i$  then solving

$$\min \sum_{i=1}^{\infty} x_i^2, \sum_{i=1}^{\infty} x_i = K$$

gets us that  $x_1 = x_2 = \ldots = x_m$  at the optimum. Hence this cost function is reduced not only when the total number of extra blank spaces is reduces, but also when our extra blanks are distributed more evenly among the lines. This property holds when the square is replaced by any value a>1.

We are given a sequence of *n* words (different lengths)

$$badness(i, j-1) = \begin{cases} \infty & \text{if } length(i, j-1) > \text{page width} \\ (\text{page width - } length(i, j-1))^2 & \text{else} \end{cases}$$

Goal: split words into lines to minimize  $\sum badness(line k)$ k=1.2...

Which are the DP equations?

DP[i]: minimum possible cost for words[i..n-1]  $\Rightarrow$  sub-problem = suffix of [0..n-1], # of sub-problems =  $\Theta(n)$ 

Guessing: j = where to end first line, # of choices = n-i

$$cost(i,j-1)$$
 first line the rest  $DP(j)$   $DP(j)$ 

#### Recurrence:

$$DP[i] = \min\{badness(i, j-1) + DP[j], j \in i+1,...,n\}, i = 0,...,n$$

$$DP[n] = 0$$

this is known already. someone should have calculated all badness() and saved in a table

### Recurrence:

$$DP[i] = min\{badness(i, j-1) + DP[j], j \in i+1,...,n\},\ i = 0,...,n$$
 $DP[n] = 0$ 

Order of computation: n, n-1, ..., 1, 0 (topological sort)

Total time =  $\Theta(n^2)$ 

Solution = DP[0]

