

# Dynamic Programming



# Dynamic Programming

**High-level Idea:** Break a problem into smaller subproblems (like divide-and-conquer) but dividing into **many overlapping** subproblems.

The DP technique applies to problems that obey the **principle of optimality**: the overall optimal solution can be constructed from optimal solutions to smaller subproblems

# Warm-Up: Fibonacci

Recurrence for Fibonacci:  $F(n) = F(n-1) + F(n-2)$

$$F(0) = F(1) = 1$$



Given a recurrence, three ways to compute its values:

1. **Top-down Recursive:** Starting at desired input, **recurse down** to base case(s)
2. **Top-down with Memoization:** Same as naïve, but **save results** as they're computed, **reusing** already-computed results
3. **Bottom-up Table (aka Dynamic Programming):** Start from base case(s), **build up** to desired result

# Fibonacci Method 1: Top-down Recursive

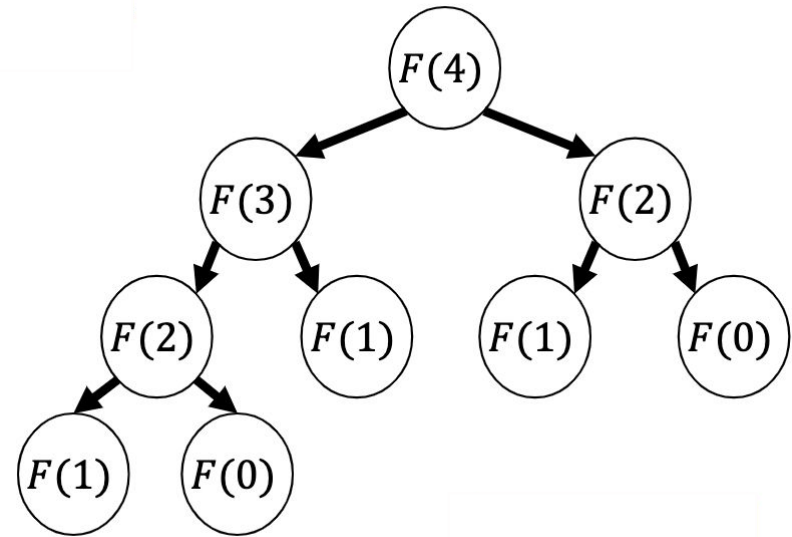
Algorithm Fib(n):

If  $n = 0$  OR  $n = 1$ :

**Return 1**

Else:

**Return**  $\text{Fib}(n-1) + \text{Fib}(n-2)$



- **Pro:** direct translation of recurrence
- **Con:** exponential running time

# Fibonacci Method 2: Top-down with Memoization

**memo** := array indexed from 0 to n

Algorithm Fib(n):

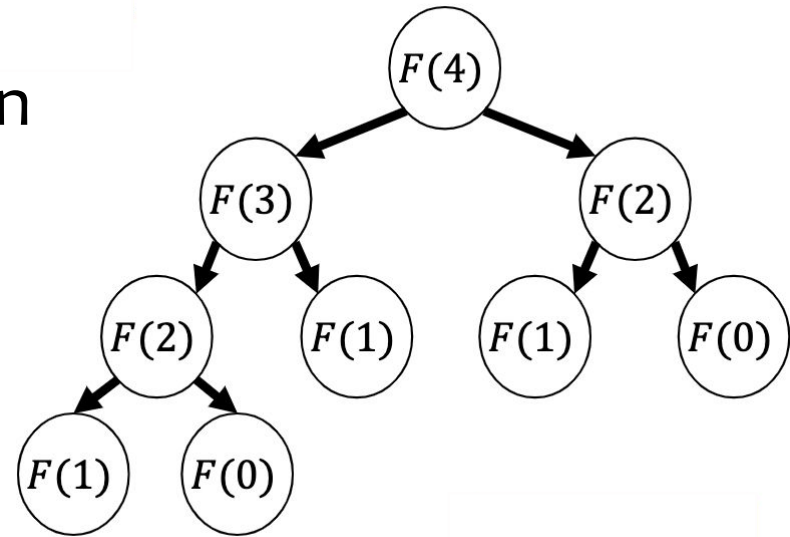
If  $n = 0$  OR  $n = 1$ :

**Return** 1

Else if **memo**(n) is empty:

**memo**(n) = Fib(n-1) + Fib(n-2)

**Return** **memo**(n)



- **Pro:** way faster
- **Con:** not clear how to analyze running time

# Fibonacci Method 3: Bottom-up Table (aka Dynamic Programming)

Algorithm Fib(n):

**table** := array indexed from 0 to n

**table**(0) = 1

**table**(1) = 1

for i = 2 to n:

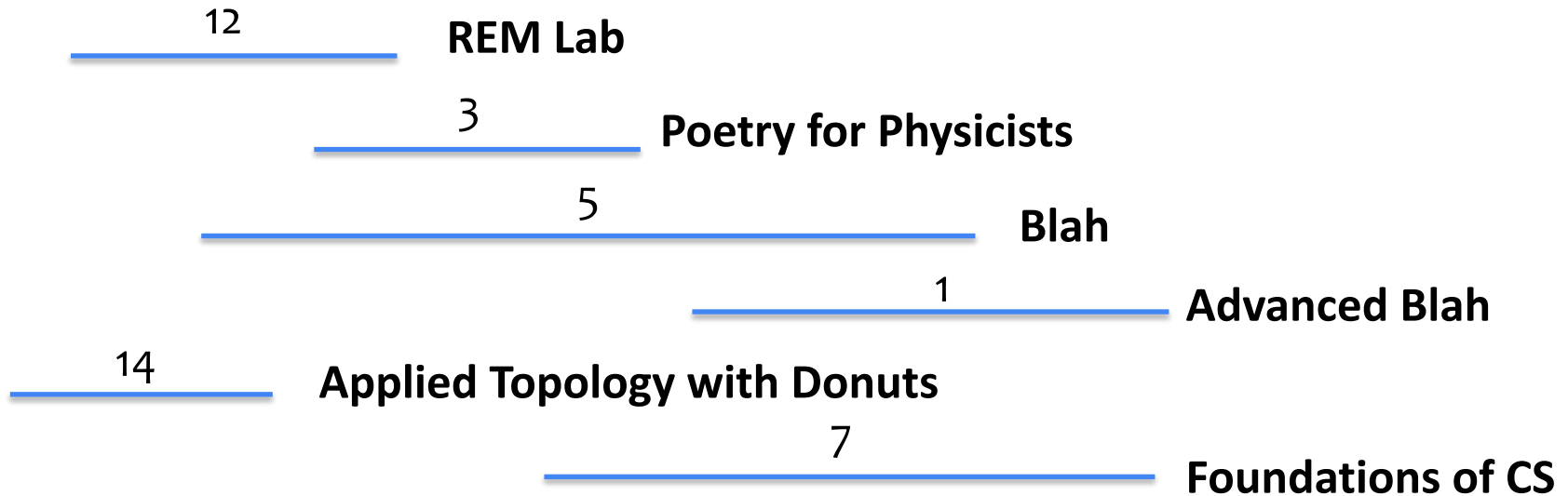
**table**(i) = **table**(i-1) + **table**(i-2)

**Return table**(n)

- **Pro:** fast, provides a roadmap for analyzing running time
- **Con:** need to translate from recurrence to table

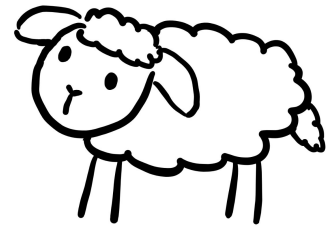
# Weighted Course Registration Problem

(aka Weighted Task Selection)



**Goal:** Choose a set of non-intersecting courses with largest total value.  
(there may be many optimal solutions, we just seek one)

I'd take the donuts course if it didn't create a hole in my schedule!



\*Let the input size be  $n = \# \text{intervals}$ . (Assume the weights are small enough that we can disregard their contribution to the input size.)

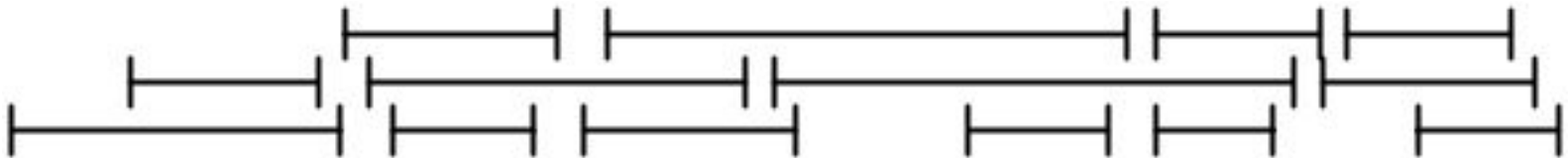
# Weighted Task Selection Recurrence

Assume the intervals  $J_1, J_2, \dots, J_n$  are given in order of **finish time**.

Let's start from  $J_n$  and work backwards.

There are two options:

- OPT has  $J_n$  (**use it!**)
- OPT doesn't have  $J_n$  (**lose it!**)





# Weighted Task Selection Recurrence

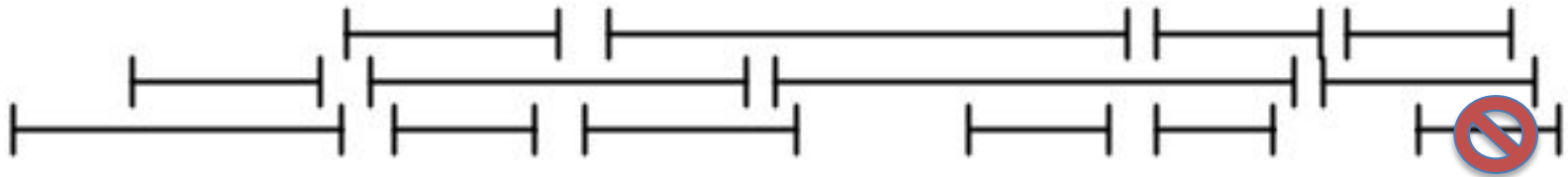
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- OPT has  $J_n$  (**use it!**)
- OPT doesn't have  $J_n$  (**lose it!**)   $\text{OTV}(J_1, \dots, J_n) = \text{OTV}(J_1, \dots, J_{n-1})$

“Optimal Task Value” i.e. the value of the optimal solution




# Weighted Task Selection Recurrence

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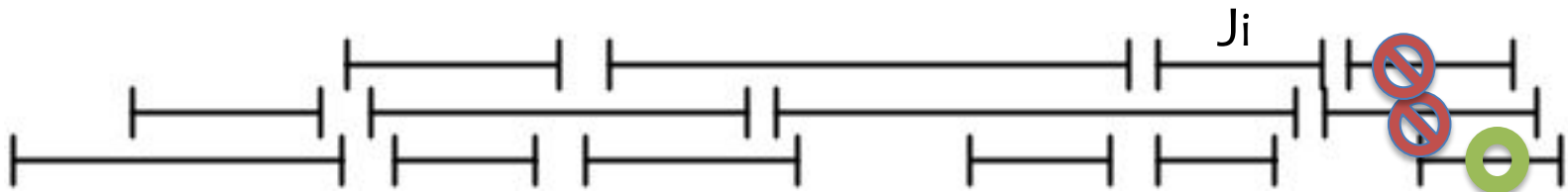
There are two options:

- OPT has  $J_n$  **(use it!)**   $\text{OTV}(J_1, \dots, J_n) = \text{val}(J_n) + \text{OTV}(J_1, \dots, J_i)$

$J_i$  is the last interval that doesn't overlap with  $J_n$

- OPT doesn't have  $J_n$  **(lose it!)**   $\text{OTV}(J_1, \dots, J_n) = \text{OTV}(J_1, \dots, J_{n-1})$

"Optimal Task Value" i.e. the value of the optimal solution



# The Final Recurrence

You could write code to implement this recurrence as an algorithm...

Algorithm OTV( $J_1, \dots, J_n$ ):

if  $n = 0$ :

**Return** 0

else:

$i$  = index of last interval (before  $J_n$ ) that doesn't overlap with  $J_n$

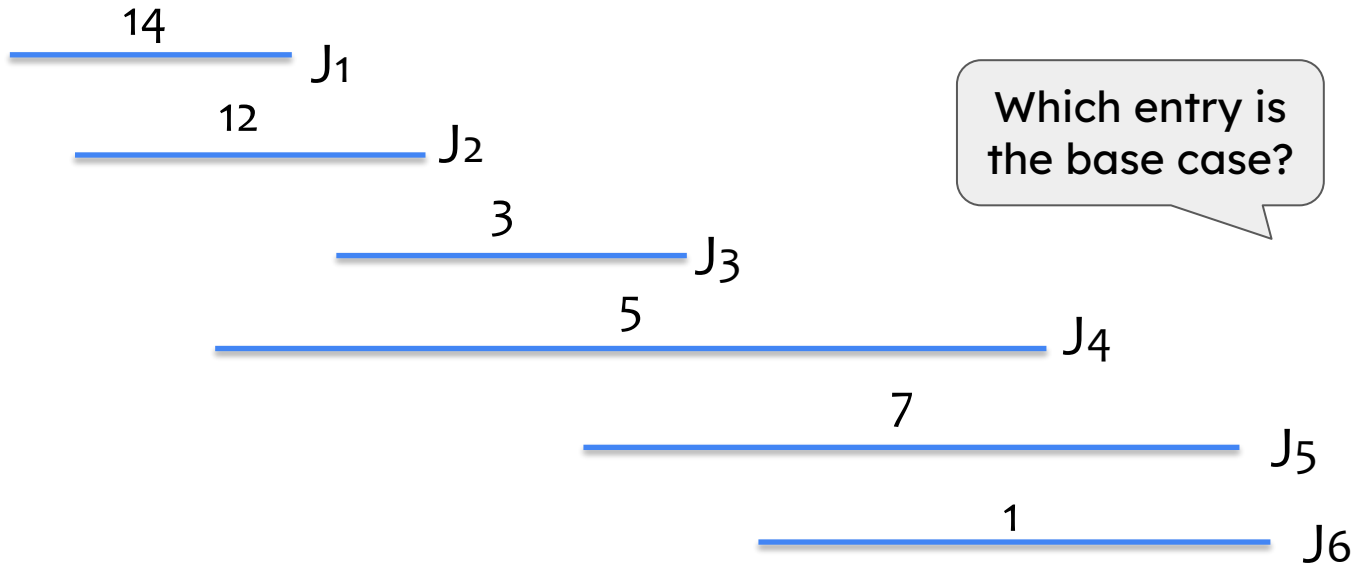
**Return**  $\max\{\text{val}(J_n) + \text{OTV}(J_1, \dots, J_i), \text{OTV}(J_1, \dots, J_{n-1})\}$

... but it would run in exponential time

# Dynamic Programming in Action!

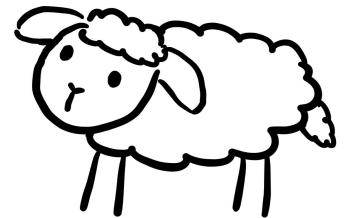
For reference:  $\text{OTV}(J_1, \dots, J_n) = \max\{\text{val}(J_n) + \text{OTV}(J_1, \dots, J_i), \text{OTV}(J_1, \dots, J_{n-1})\}$

$\text{OTV}(\emptyset)$	$\text{OTV}(J_1)$	$\text{OTV}(J_1, J_2)$	$\text{OTV}(J_1, \dots, J_3)$	$\text{OTV}(J_1, \dots, J_4)$	$\text{OTV}(J_1, \dots, J_5)$	$\text{OTV}(J_1, \dots, J_6)$



Which entry is the base case?

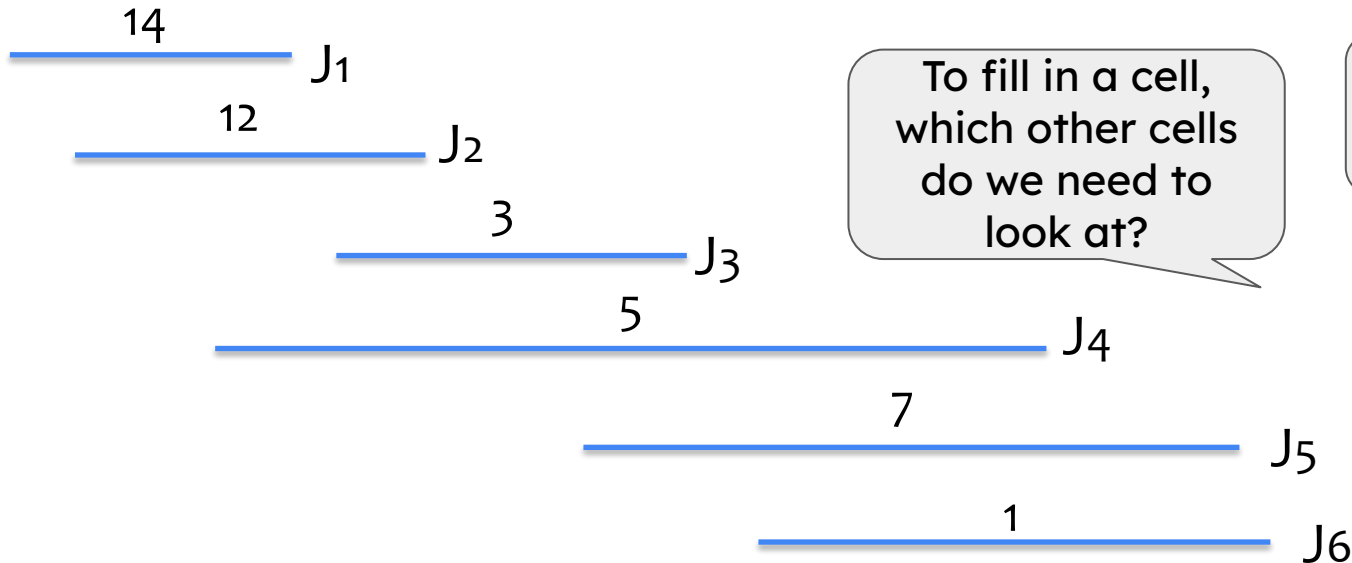
Which cell contains the final answer?



# Dynamic Programming in Action!

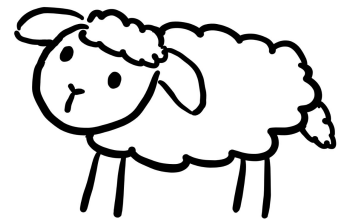
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To fill in a cell, which other cells do we need to look at?

In which order do we fill the table?



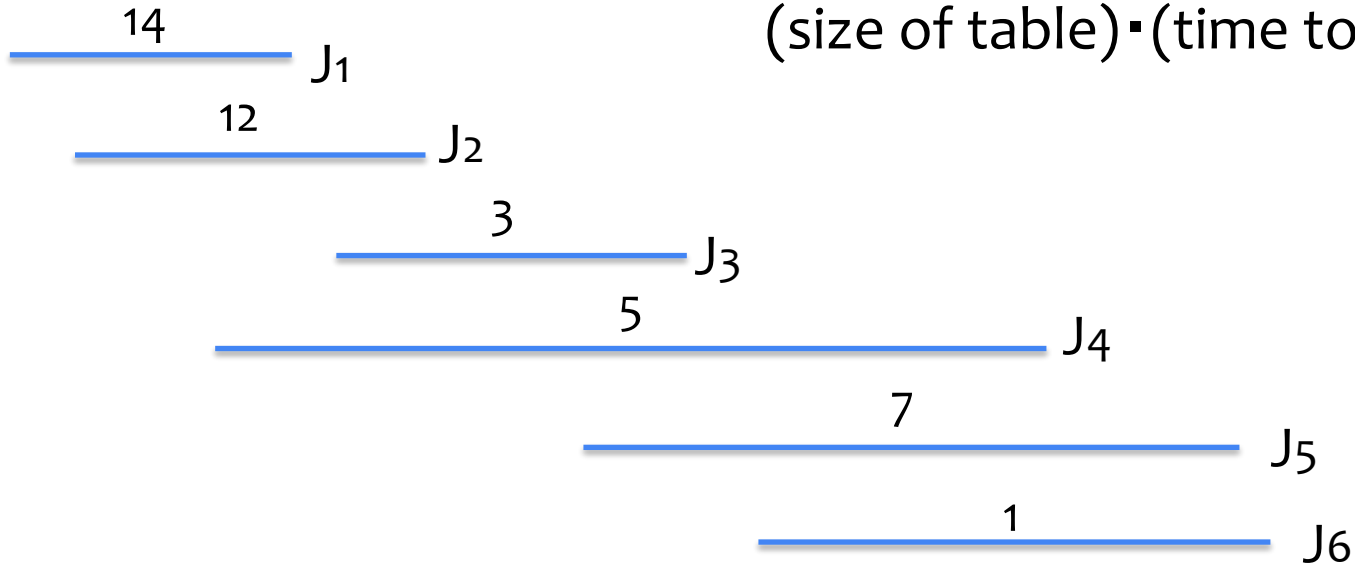
# Dynamic Programming in Action!

For reference:  $\text{OTV}(J_1, \dots, J_n) = \max\{\text{val}(J_n) + \text{OTV}(J_1, \dots, J_i), \text{OTV}(J_1, \dots, J_{n-1})\}$

OTV( $\emptyset$ )	OTV( $J_1$ )	OTV( $J_1, J_2$ )	OTV( $J_1, \dots, J_3$ )	OTV( $J_1, \dots, J_4$ )	OTV( $J_1, \dots, J_5$ )	OTV( $J_1, \dots, J_6$ )

Running time =

(size of table) • (time to fill each entry)

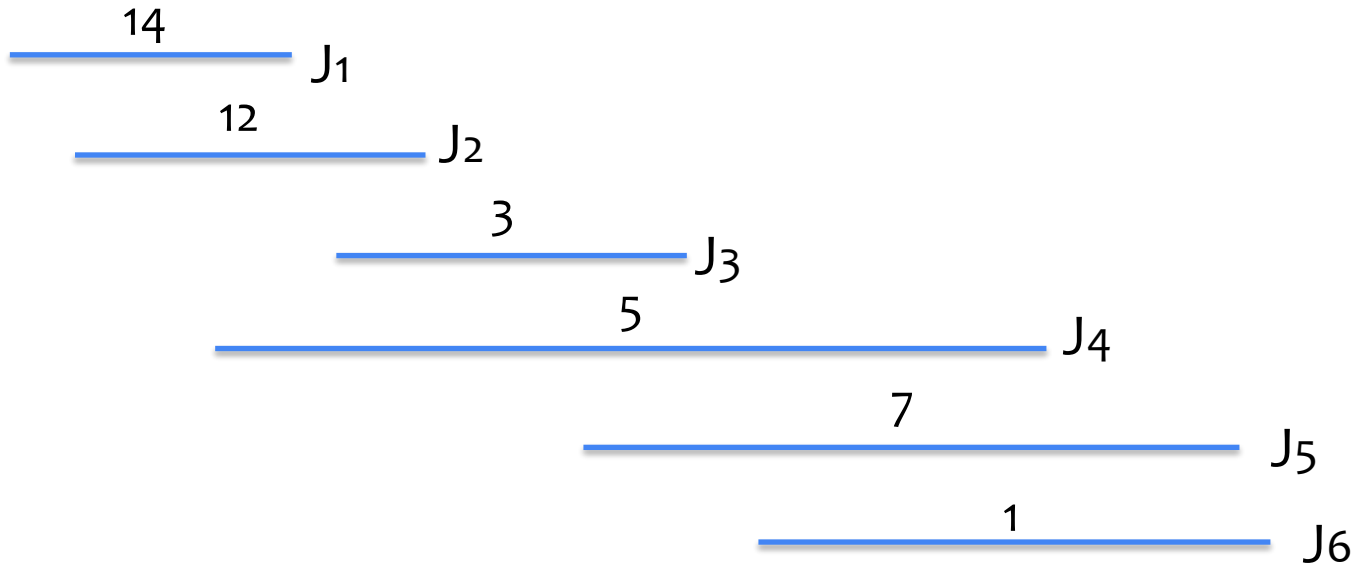


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$\text{OTV}(\emptyset)$	$\text{OTV}(J_1)$	$\text{OTV}(J_1, J_2)$	$\text{OTV}(J_1, \dots, J_3)$	$\text{OTV}(J_1, \dots, J_4)$	$\text{OTV}(J_1, \dots, J_5)$	$\text{OTV}(J_1, \dots, J_6)$

Reconstructing the solution





# The Final Pseudocode

Algorithm OTV( $J_1, \dots, J_n$ ):

**table** := array indexed from 0 to n

**table**(0) = 0

for  $k = 1$  to  $n$ :

$i$  = index of last interval (before  $J_k$ ) that doesn't overlap with  $J_k$

        // E.g. iterate through all intervals to find  $i$

**table**( $k$ ) =  $\max\{\text{val}(J_k) + \text{table}(i), \text{table}(k-1)\}$

**Return table**( $n$ )

# The DP Recipe

1. Write recurrence ← 

usually the trickiest part
2. Size of table: How many dimensions? Range of each dimension?
3. What are the base cases?
4. To fill in a cell, which other cells do I look at? In which order do I fill the table?
5. Which cell(s) contain the final answer?
6. Running time = (size of table) • (time to fill each entry)
7. To reconstruct the solution (instead of just its size) follow arrows from final answer to base case

# The Final Pseudocode

Algorithm OTV( $J_1, \dots, J_n$ ):

**table** := array indexed from 0 to n     step 2 of DP recipe

**table**(0) = 0     step 3 of DP recipe

for  $k = 1$  to  $n$ :     step 4 of DP recipe

$i$  = index of last interval (before  $J_k$ ) that doesn't overlap with  $J_k$

**table**( $k$ ) =  $\max\{\text{val}(J_k) + \text{table}(i), \text{table}(k-1)\}$

**Return table**( $n$ )     step 5 of DP recipe     steps 1,4 of DP recipe

# Why is it called “dynamic programming”?

We had a very interesting gentleman in Washington named Wilson. He was Secretary of Defense, and he actually had a pathological fear and hatred of the word, research.

[...]

His face would suffuse, he would turn red, and he would get violent if people used the term, research, in his presence.

[...]

The RAND Corporation [where Bellman worked] was employed by the Air Force, and the Air Force had Wilson as its boss, essentially. Hence, **I felt I had to do something to shield Wilson and the Air Force from the fact that I was really doing mathematics inside the RAND Corporation.**

[...]

In the first place I was interested in planning, in decision making, in thinking. But planning, is not a good word for various reasons. I decided therefore to use the word, ‘programming.’

[...]

It’s impossible to use the word, dynamic, in a pejorative sense. Try thinking of some combination that will possibly give it a pejorative meaning. It’s impossible. Thus, I thought dynamic programming was a good name. It was something not even a Congressman could object to. So I used it as an umbrella for my activities.

-Richard Bellman (introduced dynamic programming in 1953)



Another example of DP:

# Longest Increasing Subsequence (LIS)

**Input:** Array A of n numbers

**Output:** Longest increasing subsequence of A

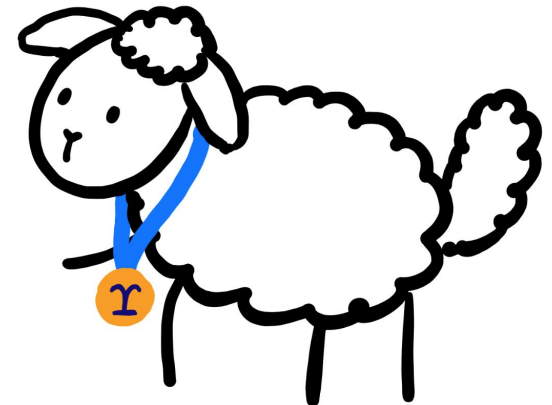
**Example:** What is the LIS of [1,4,3,7,2]?

# Recurrence for LIS

It's easy! Check it out!

$$\text{LIS}(A[1..n]) = \begin{cases} \text{LIS}(A[1..n-1]) + 1 & \text{if } A[n] > A[n-1] \text{ (use it!)} \\ \text{LIS}(A[1..n-1]) & \text{otherwise (lose it!)} \end{cases}$$

Counterexample:



# Recurrence for LIS

**Defn:** Let  $\text{END-LIS}(A[1..i])$  be the length of the LIS of  $A[1..i]$  *that ends in  $A[i]$* .

When  $A = [1, 3, 4, 2, 6]$ , what is  $\text{END-LIS}(A[1..i])$  for each  $i$ ?

**Recurrence:**

$$\text{END-LIS}(A[1..i]) = 1 + \max\{\text{END-LIS}(A[1..j]) \text{ among all } j < i \text{ with } A[j] < A[i]\}$$

(if such  $j$  exists)

Base case:  $\text{END-LIS}(A[1..i]) = 1$  if  $A[i]$  is the smallest element so far in  $A$

# Let's follow the DP Recipe

A =	3	6	1	4	5	9	2	4
END-LIS(A[1..i])								



# Pseudocode

Algorithm LIS( $A[1..n]$ ) :

**table** := array indexed from 1 to n

for  $i = 1$  to  $n$ :

if  $A[i]$  is the minimum so far: // determined by scanning  $A[1..i-1]$

**table**( $i$ ) = 1 // base case

Else:

**table**( $i$ ) =  $1 + \max\{\mathbf{table}(j) \text{ among all } j < i \text{ with } A[j] < A[i]\}$

// find  $j$  by scanning **table**

**Return**  $\max_i \mathbf{table}(i)$