

HW1 grades are out

HW2 due tonight

HW3 out by Friday, due 10/5

# CS3000: Algorithms & Data

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### Lecture 6:

- Dynamic Programming:  
Fibonacci Numbers, Interval Scheduling

Sep 25, 2018

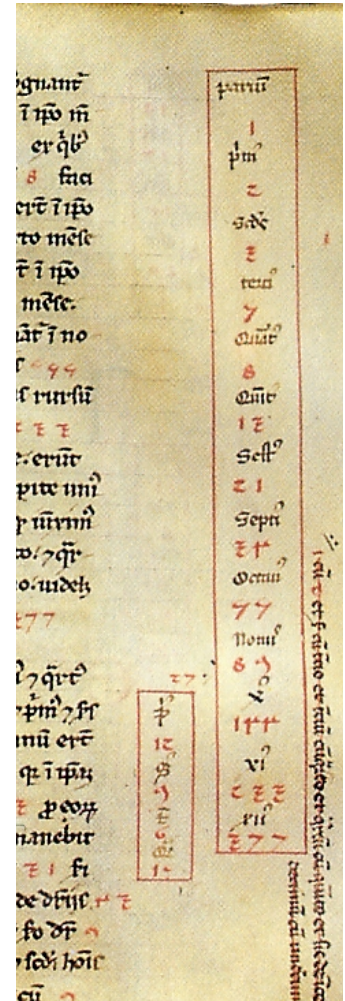
# Dynamic Programming

- Don't think too hard about the name
  - *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. -Bellman*
- Dynamic programming is careful recursion
  - Break the problem up into small pieces
  - Recursively solve the smaller pieces
  - **Key Challenge:** identifying the pieces

# Warmup: Fibonacci Numbers

# Fibonacci Numbers

- 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, ...
- $F(n) = F(n - 1) + F(n - 2)$
- $F(n) \rightarrow \phi^n \approx 1.62^n$
- $\phi = \left(\frac{1+\sqrt{5}}{2}\right)$  is the golden ratio



# Fibonacci Numbers: Take I

```
FibI(n) :  
  If (n = 0): return 0  
  ElseIf (n = 1): return 1  
  Else: return FibI(n-1) + FibI(n-2)
```

- How many recursive calls does **FibI** (n) make?

$$\cdot 2^n \quad T(n) = \# \text{ of recursive calls made by } \text{Fib}(n)$$

$$T(n) = T(n-1) + T(n-2)$$

$$T(n) \approx \phi^n \approx 1.62^n$$

# Fibonacci Numbers: Take II

“Memoization”      “Top-Down”

```
M ← empty array, M[0] ← 0, M[1] ← 1
```

```
FibII(n):
```

```
  If (M[n] is not empty): return M[n]
```

```
  Elseif (M[n] is empty):
```

```
    M[n] ← FibII(n-1) + FibII(n-2)
```

```
  return M[n]
```

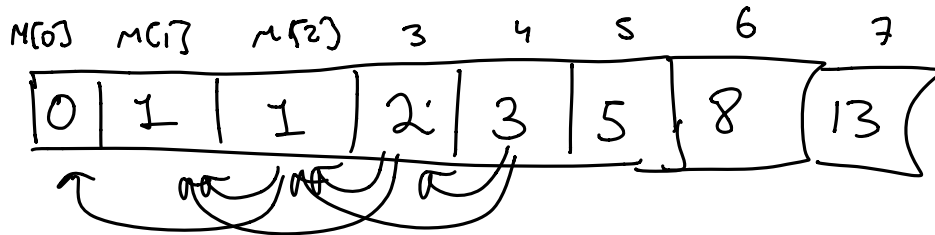
- How many recursive calls does **FibII(n)** make?
    - Only have to fill  $n-1$  entries
    - Each pair of recursive calls fills one entry
- ⇒ •  $2^{n-2}$  recursive calls       $O(n)$

# Fibonacci Numbers: Take III

"Bottom-Up"

```
FibIII(n) :  
  M[0] ← 0, M[1] ← 1  
  For i = 2, ..., n:  
    M[i] ← M[i-1] + M[i-2]  
  return M[n]
```

- What is the running time of **FibIII (n)** ?



$O(n^2)$  time algorithm (b/c  $\text{Fib}(n)$  has  $\Omega(n)$  digits)

$$\text{Fib}(n) \approx \frac{1}{\sqrt{5}} \left( \frac{1+\sqrt{5}}{2} \right)^n$$

# Fibonacci Numbers

- 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, ...
- $F(n) = F(n - 1) + F(n - 2)$
- Solving the recurrence recursively takes  $\approx 1.62^n$  time
  - Problem: Recompute the same values  $F(i)$  many times
- Two ways to improve the running time
  - Remember values you've already computed ("top down")
  - Iterate over all values  $F(i)$  ("bottom up")
- **Fact:** Can solve even faster using Karatsuba's algorithm!



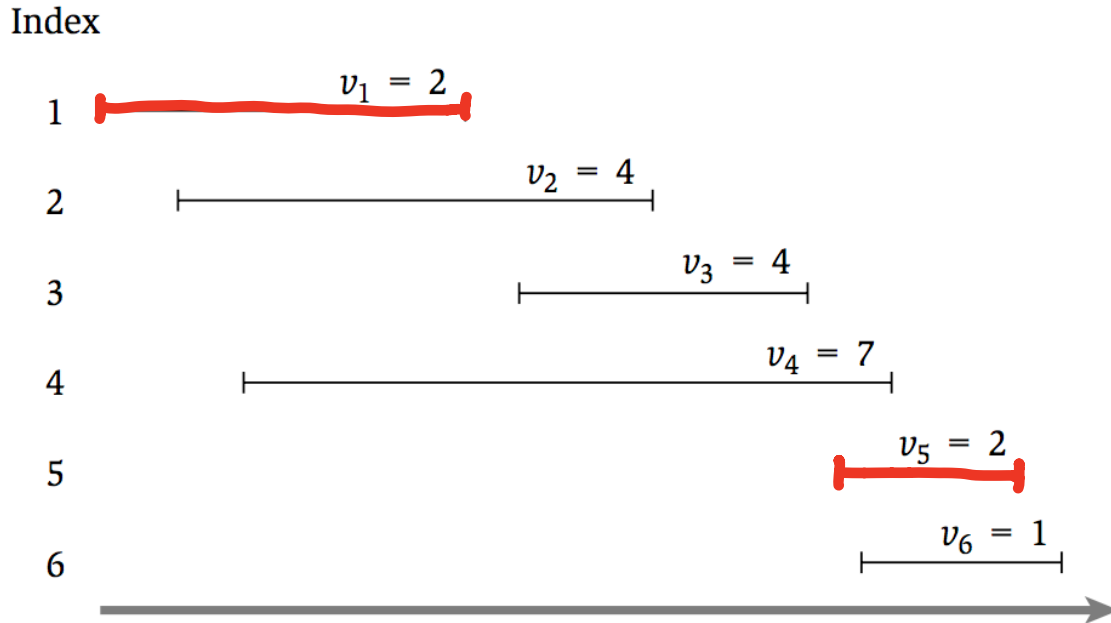
# Dynamic Programming: Interval Scheduling

# Interval Scheduling

- How can we optimally schedule a resource?
  - This classroom, a computing cluster, ...
- **Input:**  $n$  intervals  $(s_i, f_i)$  each with value  $v_i$ 
  - Assume intervals are sorted so  $f_1 < f_2 < \dots < f_n$
- **Output:** a compatible schedule  $S$  maximizing the total value of all intervals
  - A **schedule** is a subset of intervals  $S \subseteq \{1, \dots, n\}$
  - A schedule  $S$  is **compatible** if no  $i, j \in S$  overlap
  - The **total value** of  $S$  is  $\sum_{i \in S} v_i$

# Interval Scheduling

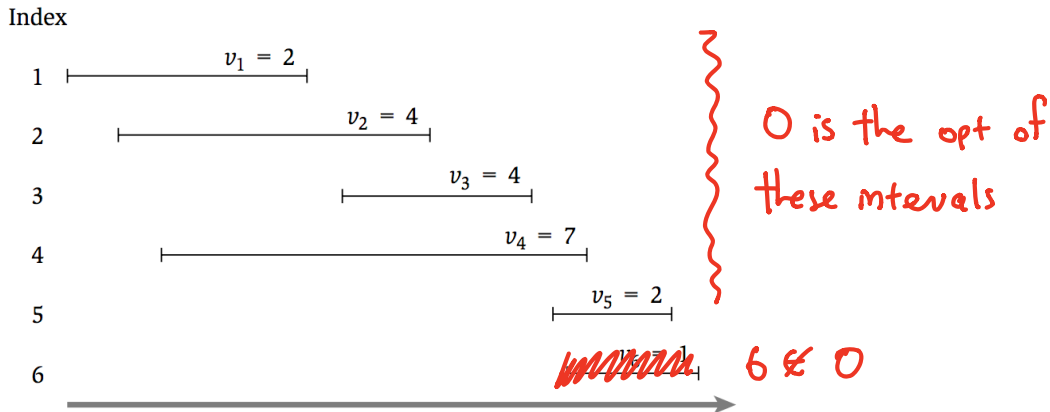
$$S = \{1, 5\} \quad \text{value}(S) = v_1 + v_5 \\ = 4$$



# A Recursive Formulation

- Let  $O$  be the **optimal** schedule
- **Case 1:** Final interval is not in  $O$  (i.e.  $6 \notin O$ )
  - Then  $O$  must be the optimal solution for  $\{1, \dots, 5\}$

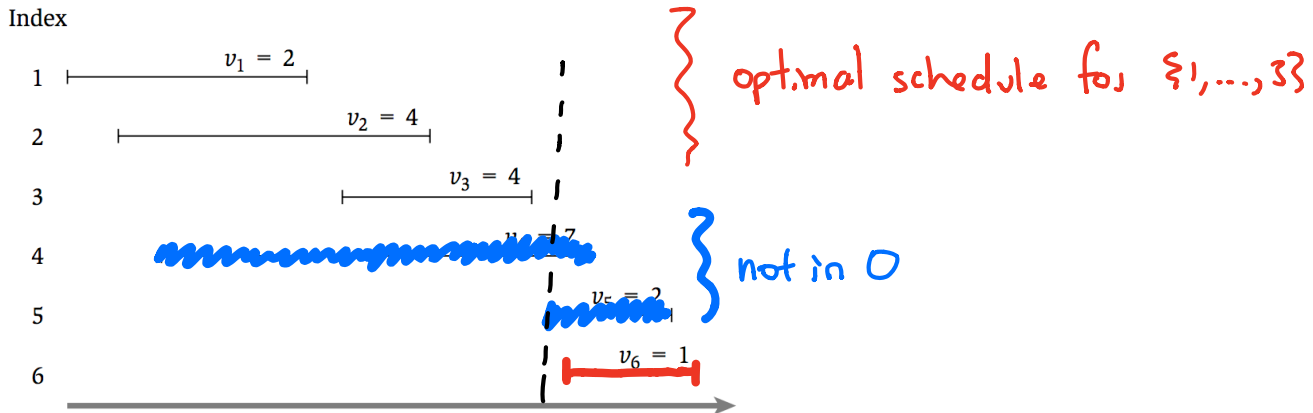
If  $O$  were not the optimal of  $\{1, \dots, 5\}$  and  $6 \notin O$ , then the opt of  $\{1, \dots, 5\}$  is better than  $O$ .



# A Recursive Formulation

- Let  $O$  be the **optimal** schedule
- **Case 2:** Final interval is in  $O$  (i.e.  $6 \in O$ )
  - Then  $O$  must be  $\{6\} +$  the optimal solution for  $\{1, \dots, 3\}$

$O$  is either  $\{6\} + \text{opt}(\{1, 2, 3\})$   
 or  $\text{opt}(\{1, \dots, 5\})$



# A Recursive Formulation

$O_n$  is the thing we want

- Let  $O_i$  be the **optimal schedule** using only the intervals  $\{1, \dots, i\}$
- **Case 1:** Final interval is not in  $O_i$  ( $i \notin O_i$ )  $O_i = O_{i-1}$ 
  - Then  $O_i$  must be the optimal solution for  $\{1, \dots, i-1\}$
- **Case 2:** Final interval is in  $O$  ( $i \in O_i$ )  $O_i = \{i\} + O_{p(i)}$ 
  - Assume intervals are sorted so that  $f_1 < f_2 < \dots < f_n$
  - Let  $p(i)$  be the largest  $j$  such that  $f_j < s_i$
  - Then  $O_i$  must be  $\{i\} +$  the optimal solution for  $\{1, \dots, p(i)\}$

If  $\text{value}(O_{i-1}) > v_i + \text{value}(O_{p(i)})$  then  $i$  is not in  $O_i$

Else  $i$  is in  $O_i$

# A Recursive Formulation

$$\curvearrowright \text{OPT}(i) = \text{value}(O_i)$$

- Let  $OPT(i)$  be the **value of the optimal schedule** using only the intervals  $\{1, \dots, i\}$
- **Case 1:** Final interval is not in  $O_i$  ( $i \notin O_i$ )  $OPT(i) = OPT(i-1)$ 
  - Then  $O$  must be the optimal solution for  $\{1, \dots, i-1\}$
- **Case 2:** Final interval is in  $O_i$  ( $i \in O_i$ )  $OPT(i) = v_i + OPT(p(i))$ 
  - Assume intervals are sorted so that  $f_1 < f_2 < \dots < f_n$
  - Let  $p(i)$  be the largest  $j$  such that  $f_j < s_i$
  - Then  $O$  must be  $i$  + the optimal solution for  $\{1, \dots, p(i)\}$

$$\bullet \text{OPT}(i) = \max\{\text{OPT}(i-1), v_i + \text{OPT}(p(i))\}$$

$$\bullet \text{OPT}(0) = 0, \text{OPT}(1) = v_1$$

Algorithmically the same as computing Fib #s

# Interval Scheduling: Take I

Assuming values  $p(n)$  are already computed

```
// All inputs are global vars
```

```
FindOPT(n):
```

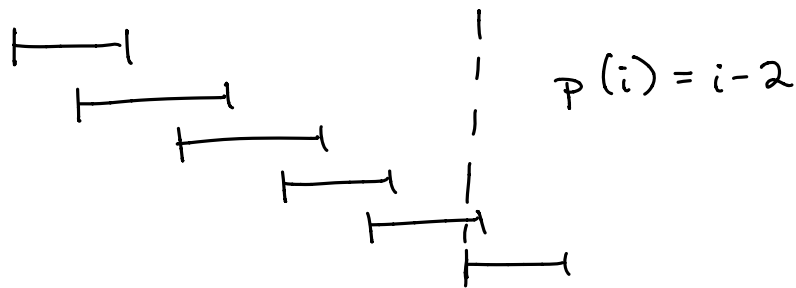
```
  if (n = 0): return 0
```

```
  elseif (n = 1): return  $v_1$ 
```

```
  else:
```

```
    return  $\max\{\text{FindOPT}(n-1), v_n + \text{FindOPT}(p(n))\}$ 
```

- What is the running time of **FindOPT** (n) ?



At least  $1.62^n$  recursive calls



# Interval Scheduling: Take II

```
// All inputs are global vars
M ← empty array, M[0] ← 0, M[1] ← u v1
FindOPT(n):
  if (M[n] is not empty): return M[n]
  else:
    M[n] ← max{FindOPT(n-1), vn + FindOPT(p(n))}
  return M[n]
```

- What is the running time of **FindOPT(n)**?

$$(n-1 \text{ entries to fill}) \times (2 \text{ calls per entry}) = 2n-2$$

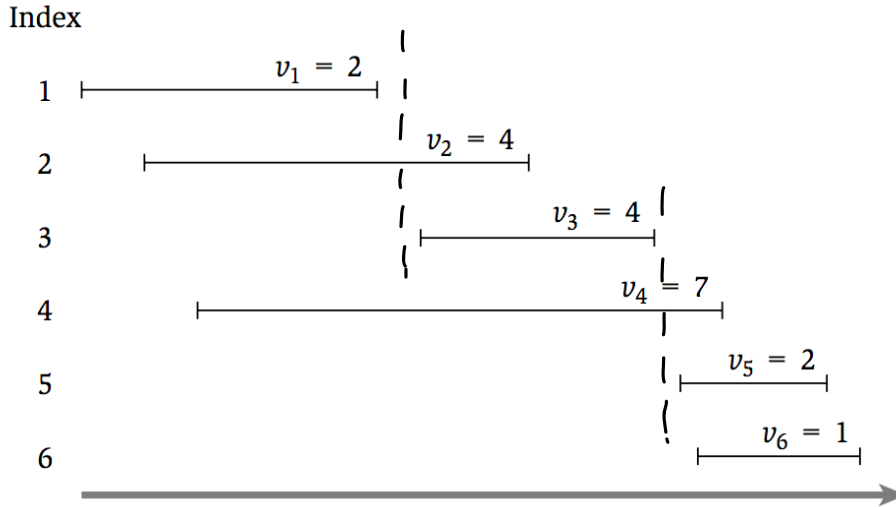
$$O(n) \text{ time } \left( \begin{array}{l} + O(n \log n) \text{ to sort if necessary} \\ + O(n) \text{ to compute } p(1) \dots p(n) \end{array} \right)$$

# Interval Scheduling: Take II

$$M[4] = \max \{ M[3], 7 + M[0] \}$$

$$M[5] = \max \{ M[4], 2 + M[3] \}$$

$$M[6] = \max \{ M[5], 1 + M[3] \}$$



$$p(1) = 0$$

$$p(2) = 0$$

$$p(3) = 1$$

$$p(4) = 0$$

$$p(5) = 3$$

$$p(6) = 3$$

$$M[i] = \text{OPT}(i)$$

$$M[2] = \max \{ M[1], 4 + M[0] \}$$

$$M[3] = \max \{ M[2], 4 + M[1] \}$$

M[0]	M[1]	M[2]	M[3]	M[4]	M[5]	M[6]
0	2	4	6	7	8	8



# Interval Scheduling: Take III

"Bottom-Up Dynamic Programming"

```
// All inputs are global vars
```

```
FindOPT(n):
```

```
  M[0] ← 0, M[1] ← 1 v1
```

```
  for (i = 2, ..., n): max { M[i-1], vi + M[p(i)] }
```

```
    M[i] ← M[i-1] if M[i-1] > vi + M[p(i)]
```

```
  return M[n]
```

- What is the running time of **FindOPT(n)**?

$O(n)$  + time to sort if needed + time to compute  $p(i)$ 's

# Finding the Optimal Solution

- Let  $OPT(i)$  be the **value of the optimal schedule** using only the intervals  $\{1, \dots, i\}$
- **Case 1:** Final interval is not in  $O$  ( $i \notin O$ )
- **Case 2:** Final interval is in  $O$  ( $i \in O$ )

- $OPT(i) = \max\{OPT(i-1), v_i + OPT(p(i))\}$

If  $(OPT(i-1) > v_i + OPT(p(i)))$ :

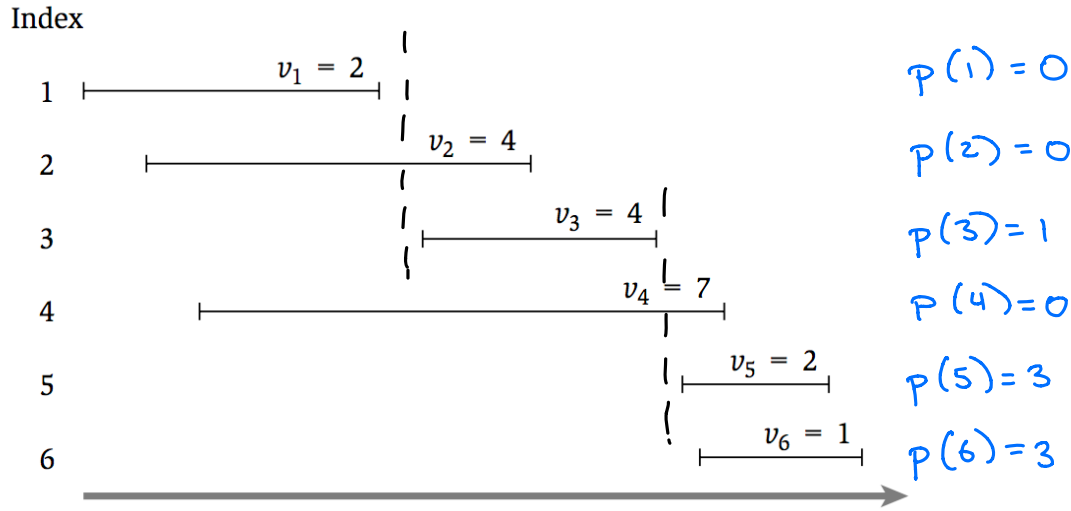
$$O_i = O_{i-1} \quad (i \notin O_i)$$

Else if  $(v_i + OPT(p(i)) > OPT(i-1))$ :

$$O_i = \{i\} + O_{p(i)} \quad (i \in O_i)$$

Else:  $O_i$  could be either  $\{i\} + O_{p(i)}$  or  $O_{i-1}$

# Interval Scheduling: Take II



$$M[i] = \text{OPT}(i)$$

$$O_6 = \{1, 3, 5\}$$

M[0]	M[1]	M[2]	M[3]	M[4]	M[5]	M[6]
0	2	4	6	7	8	8

$$O_1 = \{1\}$$

$$3 \in O$$

$$5 \in O$$

$$6 \notin O$$

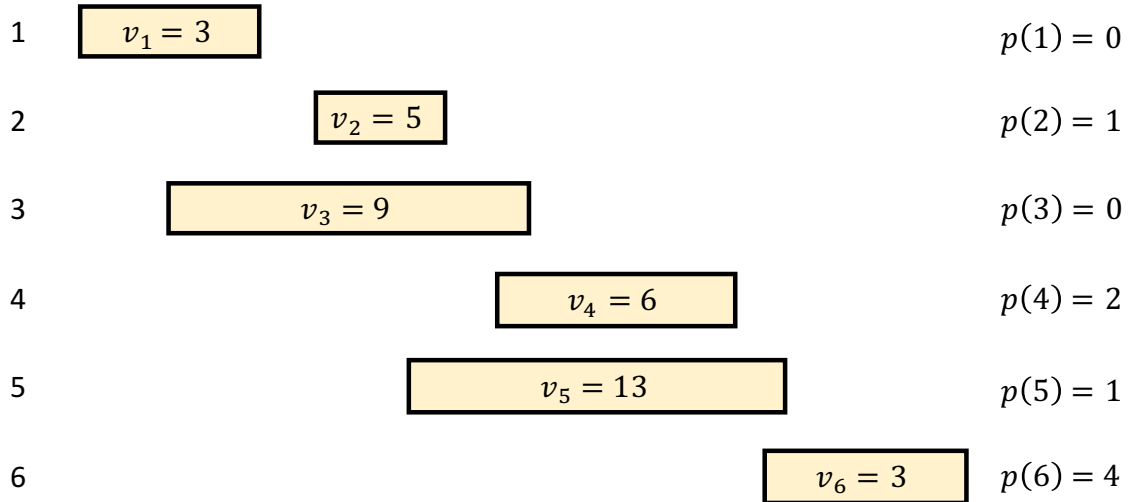
# Interval Scheduling: Take III

Completed table with value of optimum

```
// All inputs are global vars
FindSched(M,n) :
  if (n = 0): return  $\emptyset$ 
  elseif (n = 1): return {1}
  elseif ( $v_n + M[p(n)] > M[n-1]$ ):
    return {n} + FindSched(M,p(n))
  else:
    return FindSched(M,n-1)
```

- What is the running time of **FindSched(n)** ?

# Now You Try



M[0]	M[1]	M[2]	M[3]	M[4]	M[5]	M[6]

# Dynamic Programming Recap

- Express the optimal solution as a **recurrence**
  - Identify a small number of **subproblems**
  - Relate the optimal solution on subproblems
- Efficiently solve for the **value** of the optimum
  - Simple implementation is exponential time
  - **Top-Down**: store solution to subproblems
  - **Bottom-Up**: iterate through subproblems in order
- Find the **solution** using the table of **values**