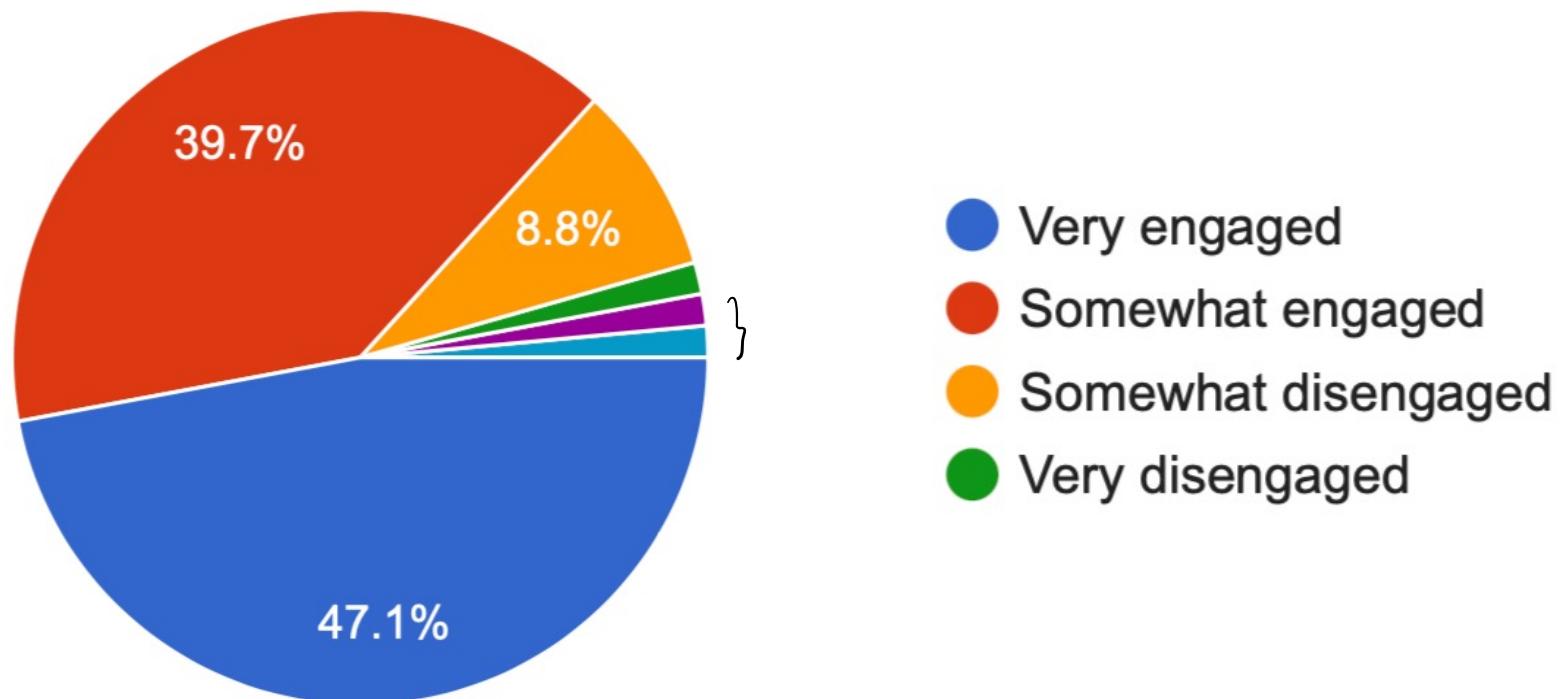


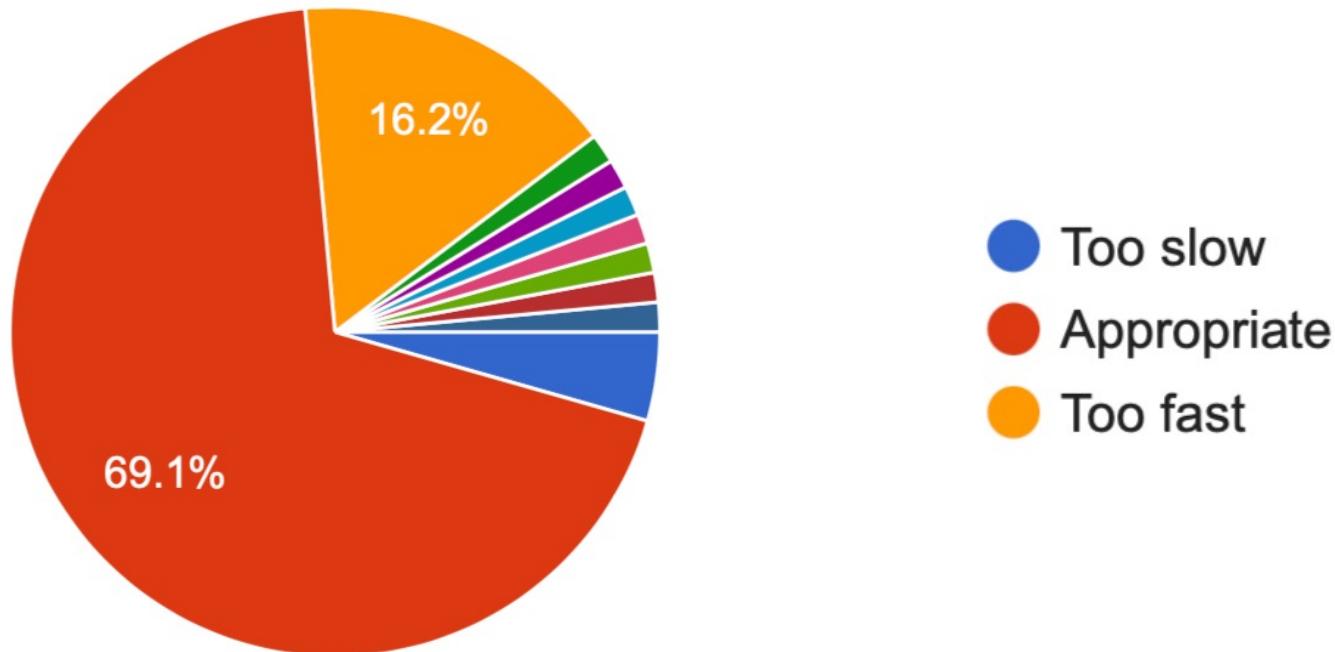
Survey Results

- How engaged do you feel in class?



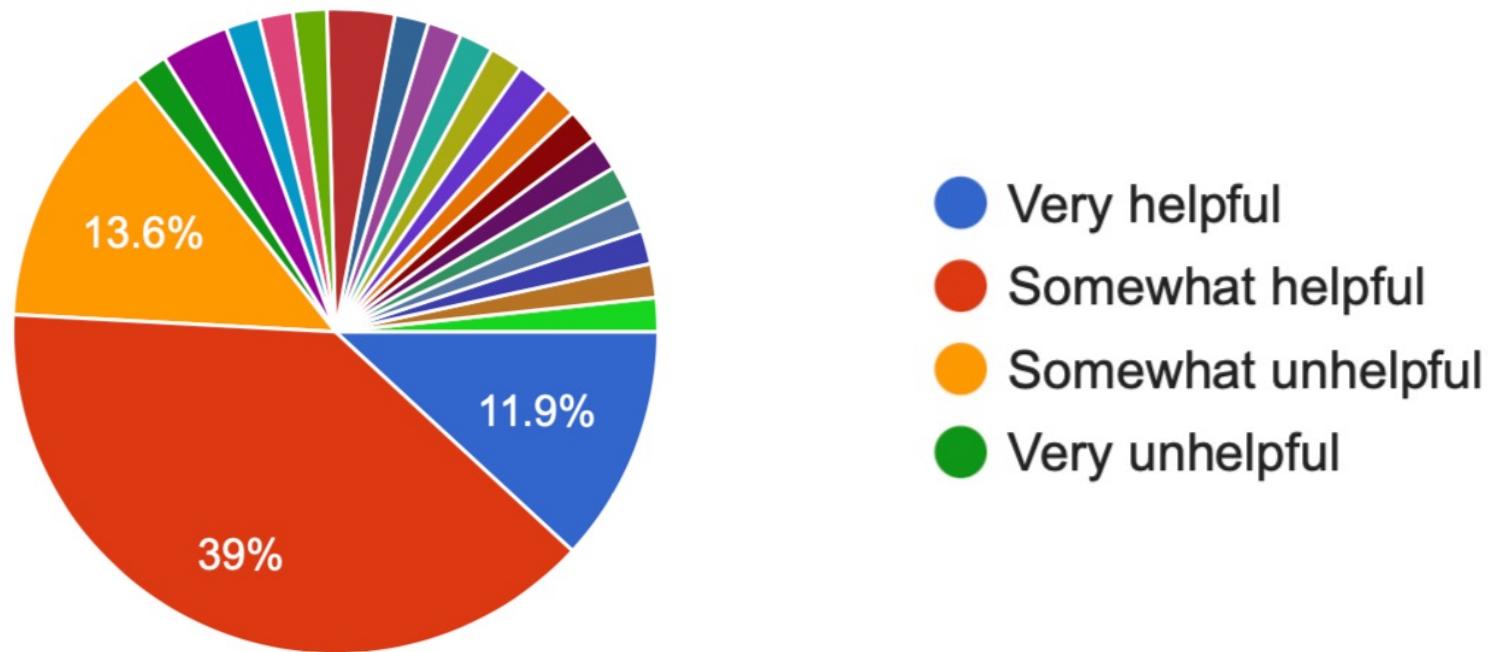
Survey Results

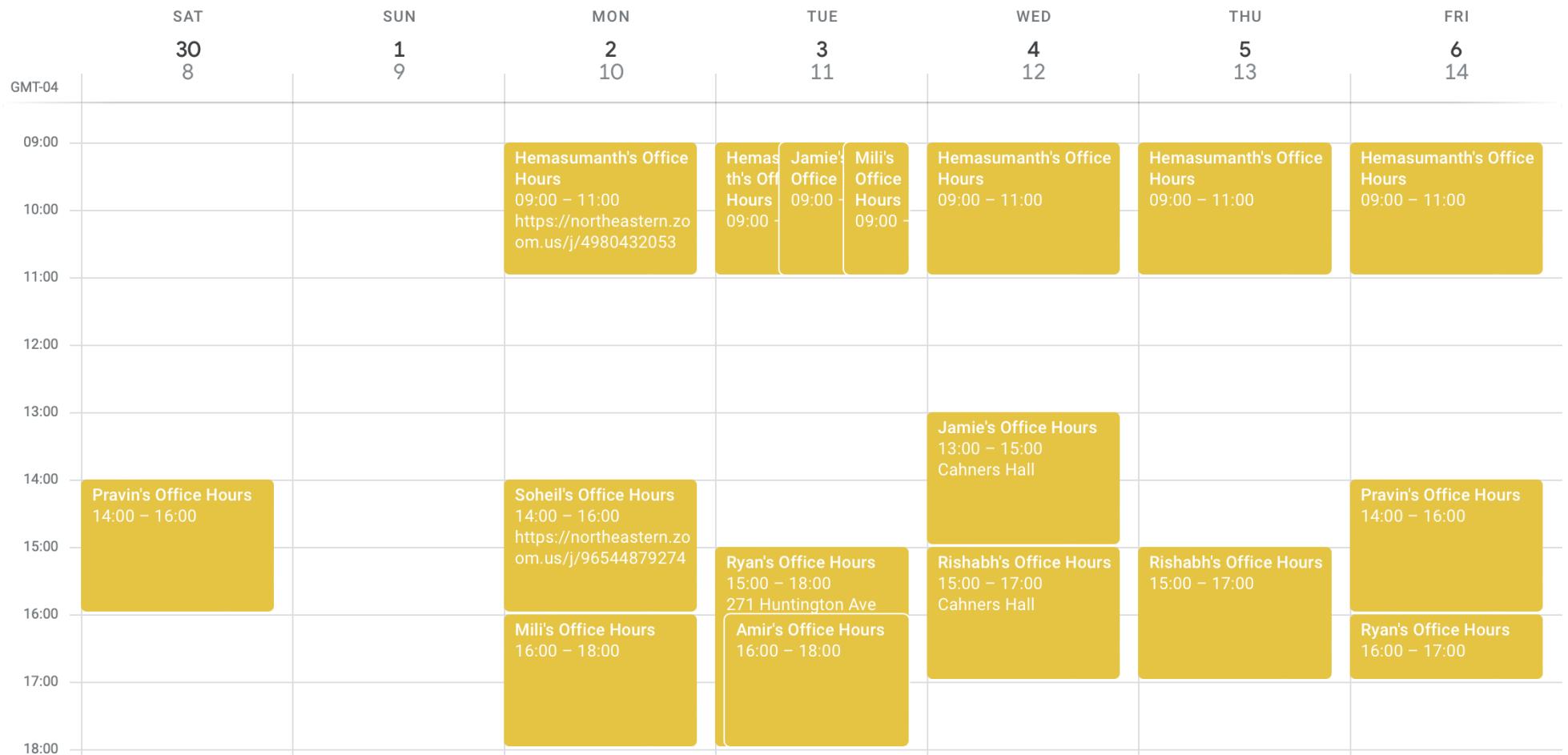
- What do you think about the pace of the lectures?



Survey Results

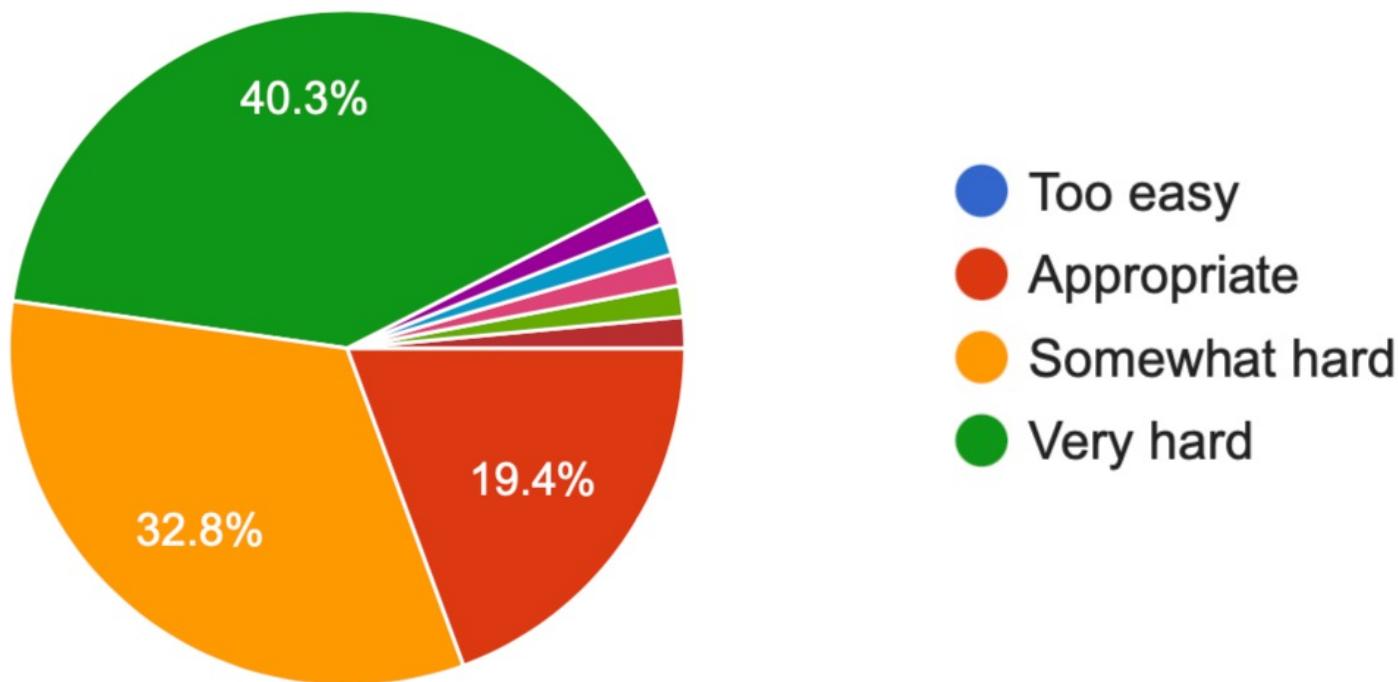
- Do you attend the office hours? If yes, have they been helpful?





Survey Results

- What do you think about the difficulty of homework 1?



Dynamic Programming Recipe

- **Recipe:**
 - (1) identify a set of **subproblems**
 - (2) relate the subproblems via a **recurrence**
 - (3) find an **efficient implementation** of the recurrence (top down or bottom up)
 - (4) **reconstruct the solution** from the DP table



Dynamic Programming

- a. Fibonacci Series
- b. Weighted Interval Scheduling

Weighted 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 $\sum_{i \in S} v_i$

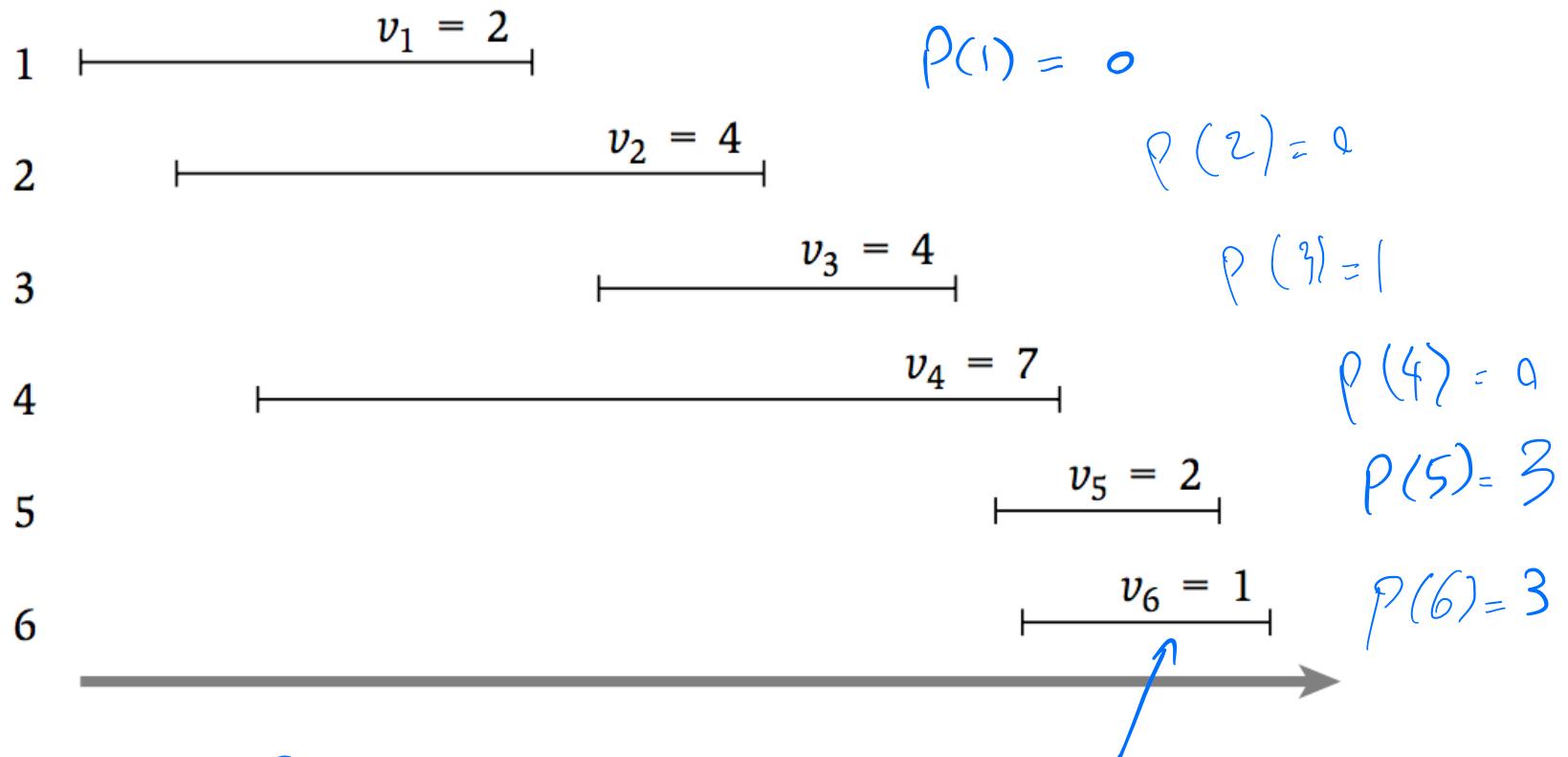


Interval Scheduling

$\rho(i)$: largest j s.t. $f_j \leq s_i$.

$$2 + 4 + 1 = 7$$

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$$O_6 = \begin{cases} O_5 \\ v_6 + \text{val}(O_{\rho(6)}) \end{cases}$$



A Recursive Formulation: Subproblems

- **Subproblems:** Let O_i be the **optimal schedule** using only the intervals $\{1, \dots, i\}$
- **Case 1:** Final interval is not in O_i ($i \notin O_i$)
 - Then O_i must be the optimal solution for $\{1, \dots, i - 1\}$
 - $O_i = O_{i-1}$
- **Case 2:** Final interval is in O_i ($i \in O_i$)
 - 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 $\{1, \dots, p(i)\}$
 - $O_i = \{i\} + O_{p(i)}$



A Recursive Formulation: Subproblems & Recurrence

- **Subproblems:** Let $OPT(i)$ be the **value of the optimal schedule** using only the intervals $\{1, \dots, i\}$ ($OPT(i) = value(O_i)$)
- **Case 1:** Final interval is not in O_i ($i \notin O_i$)
 - Then O_i must be the optimal solution for $\{1, \dots, i - 1\}$
- **Case 2:** Final interval is in O_i ($i \in O_i$)
 - 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 $\{1, \dots, p(i)\}$
- $OPT(i) = \max\{OPT(i - 1), v_i + OPT(p(i))\}$
- $OPT(0) = 0, OPT(1) = v_1$



Dynamic Programming Recipe

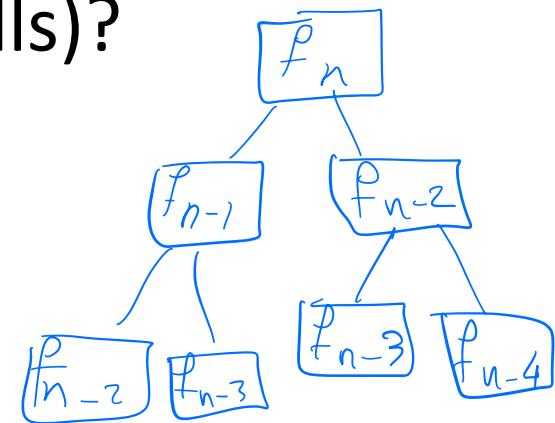
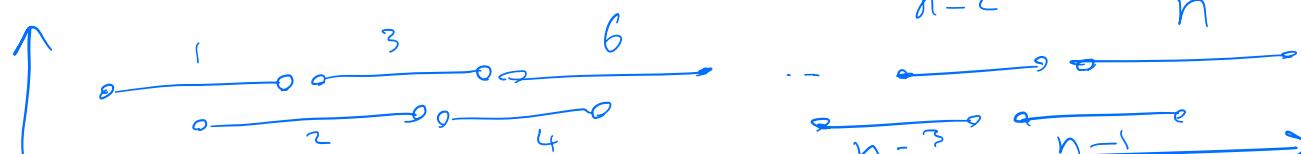
- **Recipe:**
 - (1) identify a set of **subproblems**
 - (2) relate the subproblems via a **recurrence**
 - (3) find an **efficient implementation** of the recurrence (top down or bottom up)
 - (4) **reconstruct the solution** from the DP table



Interval Scheduling: Straight Recursion

```
FindOPT(n) :  
    if (n = 0): return 0  
    elseif (n = 1): return v1  
    else:  
        return max{FindOPT(n-1), vn + FindOPT(p(n))}
```

- What is the worst-case running time of **FindOPT(n)** (how many recursive calls)?



Interval Scheduling: Memoized

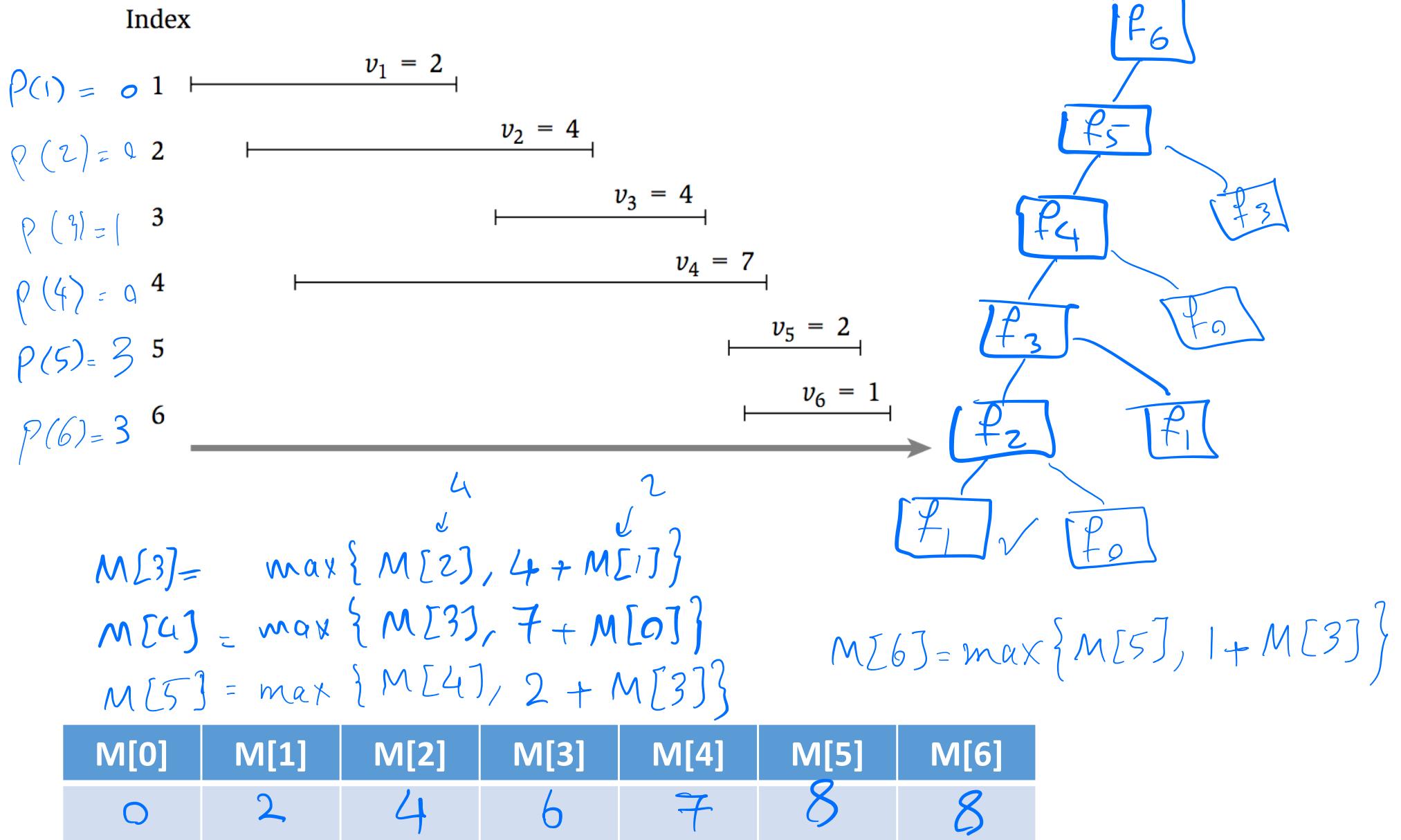
```
// All inputs are global vars
M ← empty array, M[0] ← 0, M[1] ← v1
FindOPT(n) :
    if (M[n] is not empty): return M[n]
    else:
        M[n] ← max{FindOPT(n-1), vn + FindOPT(p(n)) }
    return M[n]
```

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

O(n)



Interval Scheduling: Memoized



Interval Scheduling: Bottom Up

```
FindOPT(n) :  
    M[0] ← 0, M[1] ← v1  
    for (i = 2, ..., n) :  
        M[i] ← max{M[i-1], vi + M[p(i)]}  
    return M[n]
```

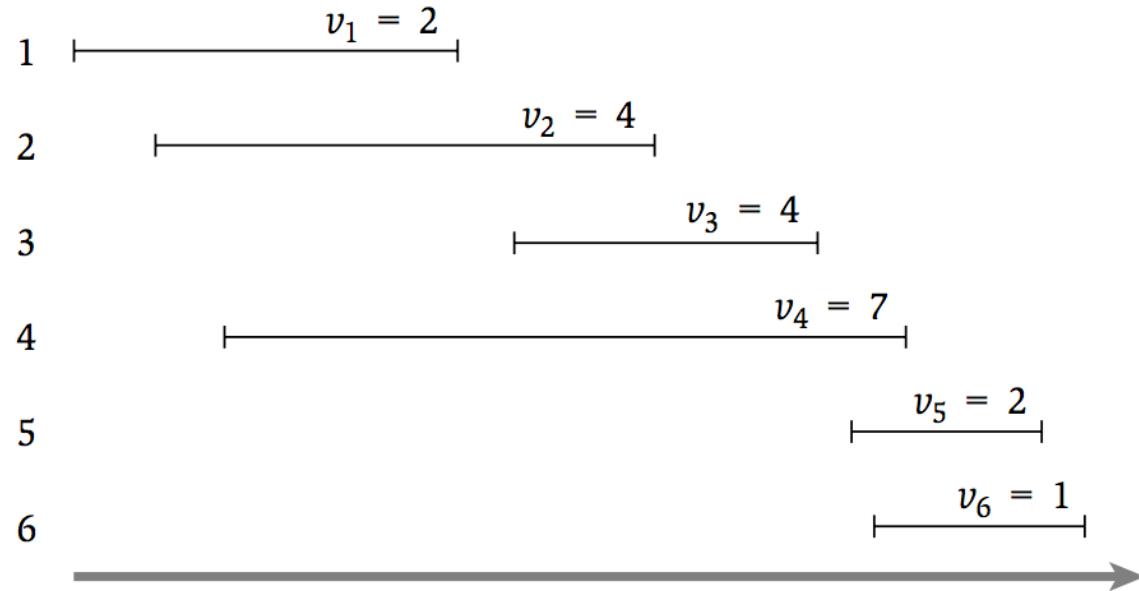
$O(n)$

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



Interval Scheduling: Bottom Up

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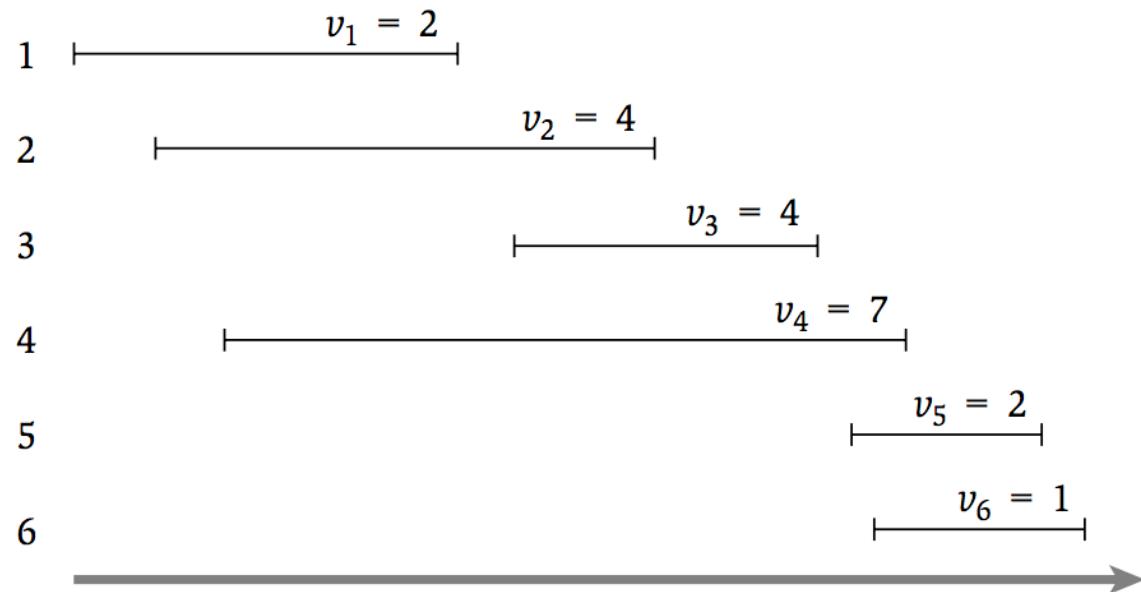
M[0]	M[1]	M[2]	M[3]	M[4]	M[5]	M[6]
0	2	4				



Finding the Optimal Solution

- But we want a schedule, not a value!

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



Dynamic Programming Recipe

- **Recipe:**

- (1) identify a set of **subproblems**
- (2) relate the subproblems via a **recurrence**
- (3) find an **efficient implementation** of the recurrence (top down or bottom up)

{ (4) **reconstruct the solution** from the DP table



Finding the Optimal Solution

DP Table which we assume is already filled up



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)
```

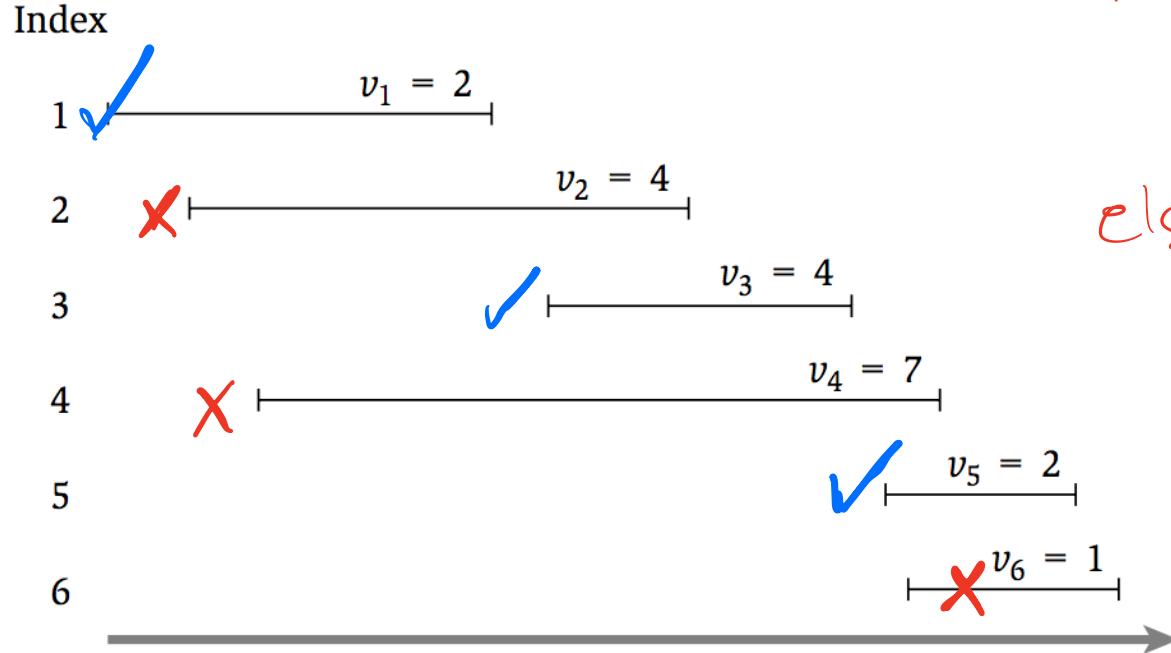
F_n
↓
 F_{n-1}
↓
 $F_{P(n-1)}$
↓
 \vdots
 $F_{[0]}$

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

$O(n)$



Finding the Optimal Solution



If $v_6 + M[P[6]] > M[5]$
 1 6 8
 return $\{6\} + FO(P[6])$

else
 return $FO(6-1)$

$v_5 + M[P[5]] > M[4]$
 2 6 7

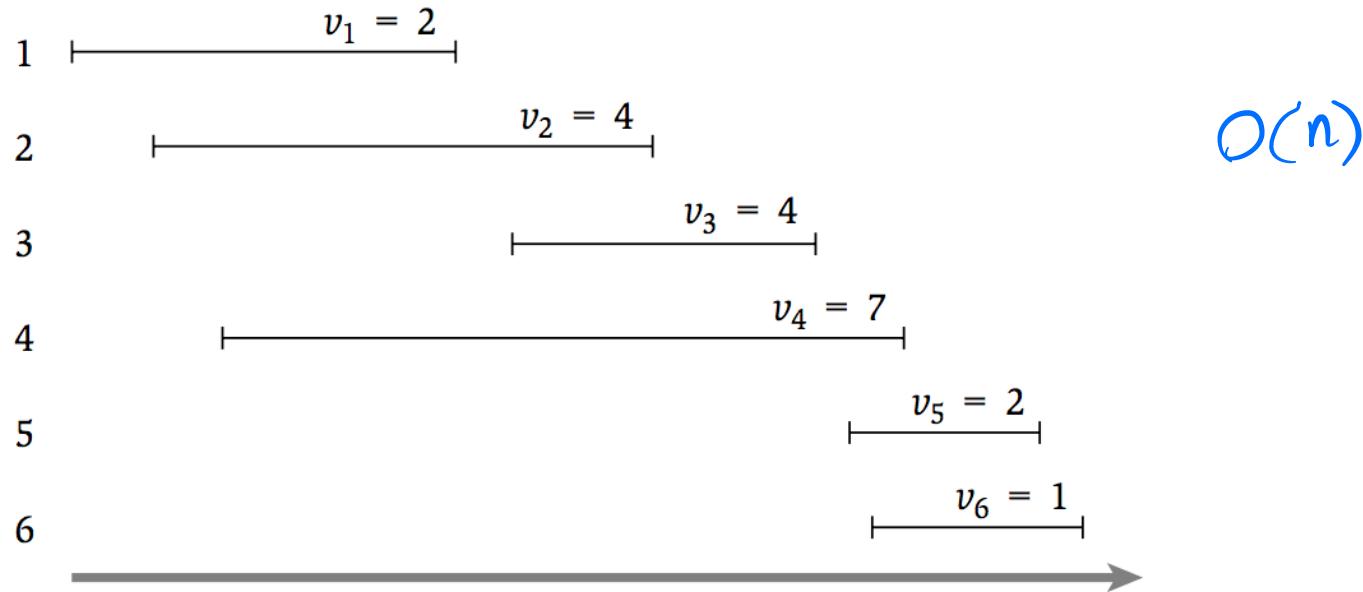
$v_3 + M[P[3]] > M[2]$
 4 2 4

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



How much space is used?

Index



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

Now You Try

1	$v_1 = 2$	$p(1) = 0$
2	$v_2 = 1$	$p(2) = 1$
3	$v_3 = 6$	$p(3) = 0$
4	$v_4 = 5$	$p(4) = 2$
5	$v_5 = 9$	$p(5) = 1$
6	$v_6 = 2$	$p(6) = 4$

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, but top-down and bottom-up are linear time
 - **Top-Down:** recursive, store solution to subproblems
 - **Bottom-Up:** iterate through subproblems in order
- Find the **solution** using the table of **values**



Dynamic Programming

- a. Fibonacci Series
- b. Weighted Interval Scheduling
- c. Knapsack

(source: Wikipedia)

The Knapsack Problem

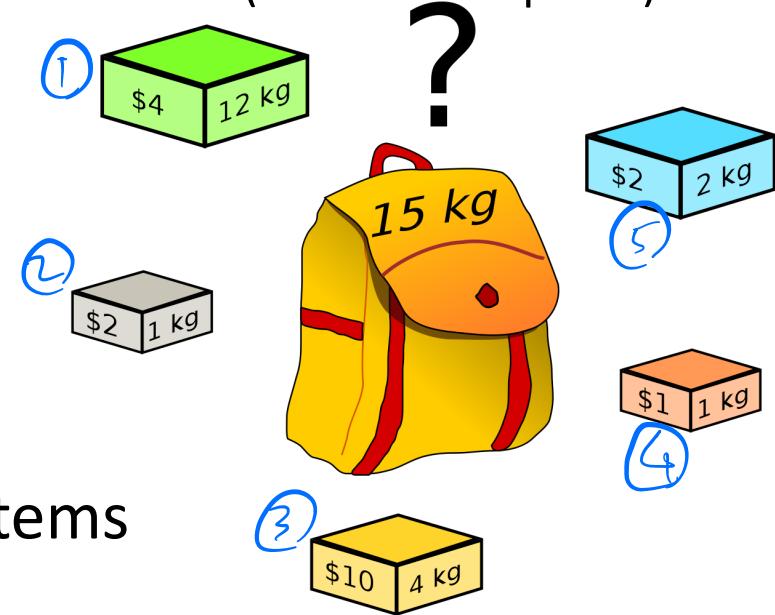
- **Input:** n items for your knapsack
 - value v_i and a weight $w_i \in \mathbb{N}$ for n items
 - capacity of your knapsack $T \in \mathbb{N}$
- **Output:** the most valuable subset of items that fits in the knapsack

- Subset $S \subseteq \{1, \dots, n\}$
- Value $V_S = \sum_{i \in S} v_i$ as large as possible
- Weight $W_S = \sum_{i \in S} w_i$ at most T

- **Want:** $\text{argmax}_{S \subseteq \{1, \dots, n\}} V_S$ s.t. $W_S \leq T$

- **SubsetSum:** $v_i = w_i$,

- **TugOfWar:** $v_i = w_i, T = \frac{1}{2} \sum_i v_i$



$$n = 5 \quad T = 15$$

$$v_1 = 4 \quad w_1 = 12$$

$$v_2 = 2 \quad w_2 = 1$$

$$v_3 = 10 \quad w_3 = 4$$

$$v_4 = 1 \quad w_4 = 1$$

$$v_5 = 2 \quad w_5 = 2$$

Do we really need DP?

Items with large $\frac{v_i}{w_i}$ seem like good choices...

Ex. $T = 8$, $(v_1 = 6, w_1 = 5)$, $(v_2 = 4, w_2 = 4)$, $(v_3 = 4, w_3 = 4)$



- Strategy 1: Repeatedly pick items that fit with largest $\frac{v_i}{w_i}$

we only pick item 1 and gain a value of 6

- Is this optimal?

opt is {2,3} which gives value 8.