CS 401

Dynamic Programming

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Stuff

Homework 3 is due this Friday March 29 11:59pm

Submission is now open (at Gradescope)

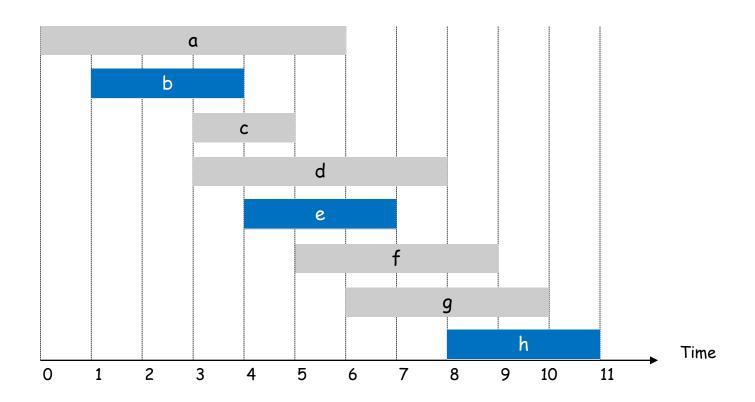
Course survey

- https://forms.gle/4gUVgQQhDGaFR2ge8
- Anonymous survey
- Collect the feedback regarding lectures/homework/midterm exam
- Is the homework/exam too easy or too hard?
- Your feedback will be used to adjust the difficulty of the rest homework and final exam

Weighted Interval Scheduling

Weighted Interval Scheduling

- Job j starts at s(j) and finishes at f(j) and has weight w_j
 - •Two jobs compatible if they don't overlap.
 - •Goal: find maximum weight subset of mutually compatible jobs.

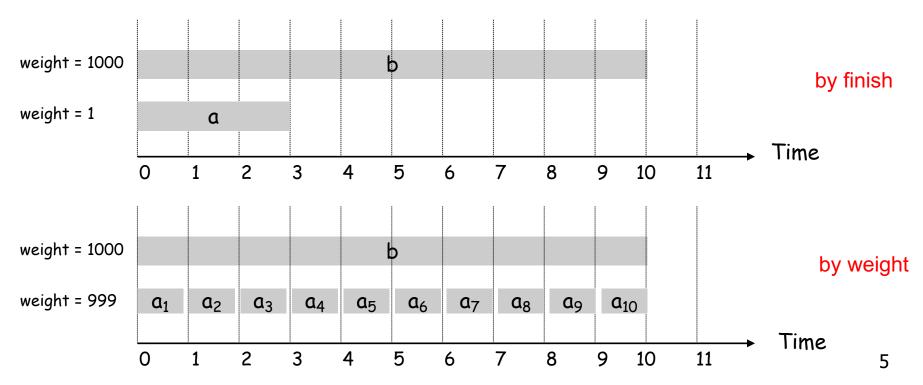


Unweighted Interval Scheduling: Review

Recall: Greedy algorithm works if all weights are 1:

- Consider jobs in ascending order of finishing time
- Add job to a subset if it is compatible with prev added jobs.

Observation: Greedy ALG fails spectacularly if arbitrary weights are allowed:



Weighted Job Scheduling by Induction

Suppose 1, ..., n are

This idea works for any Optimization problem.

IH: Suppose jobs of size

For NP-hard problems there is no ordering to reduce # subproblems

IS: Goal: For any n

Case 1: Job n is not in Op 1.

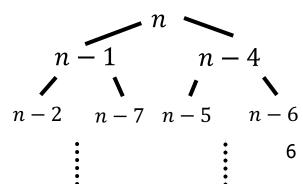
-- Then, just return OPT of 1, ..., n-1.

Case 2: Job n is in OPT.

-- Then, delete all jobs not compatible with n and recurse.

Q: Are we done?

A: No, How many subproblems are there? Potentially 2^n all possible subsets of jobs.



Take best of the two

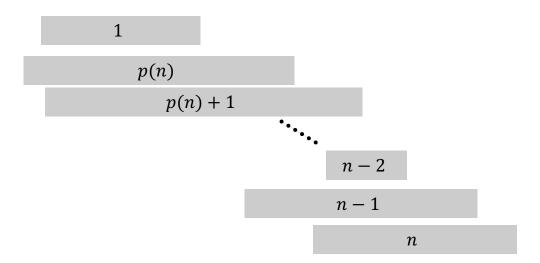
Sorting to Reduce Subproblems

Sorting Idea: Label jobs by finishing time $f(1) \le \cdots \le f(n)$

IS: For jobs 1, ..., n we want to compute OPT

Case 1: Suppose OPT has job n.

- So, all jobs i that are not compatible with n are not OPT
- Let p(n) =largest index i < n such that job i is compatible with n.
- Then, we just need to find OPT of 1, ..., p(n)



Sorting to reduce Subproblems

Sorting Idea: Label jobs by finishing time $f(1) \le \cdots \le f(n)$ IS: For jobs $1, \dots, n$ we want to compute OPT

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- Let p(n) =largest index i < n such that job i is compatible with n.
- Then, we just need to find OPT of 1, ..., p(n)

Case 2: OPT does not select job n.

• Then, OPT is just the OPT of 1, ..., n-1

Take best of the two

Q: Have we made any progress?

A: Yes! This time every subproblem is of the form 1, ..., i for some i So, at most n possible subproblems.

Weighted Job Scheduling by Induction

Sorting Idea: Label jobs by finishing time $f(1) \le \cdots \le f(n)$ Def OPT(j) denote the weight of OPT solution of $1, \dots, j$

To solve OPT(j): The most important part of a correct DP; It fixes IH

Case 1: OPT(j) has job j.

- So, all jobs i that are not compatible with j are not OPT(j).
- Let p(j) = largest index i < j such that job i is compatible with j.
- So $OPT(j) = OPT(p(j)) + w_j$.

Case 2: OPT(j) does not select job j.

• Then, OPT(j) = OPT(j-1).

$$OPT(j) = \begin{cases} 0 & \text{if } j = 0\\ \max(w_j + OPT(p(j)), OPT(j-1)) & \text{o. w.} \end{cases}$$

Algorithm

```
Input: n, s(1),...,s(n) and f(1),...,f(n) and w_1,...,w_n.

Sort jobs by finish times so that f(1) \leq f(2) \leq \cdots f(n).

Compute p(1),p(2),...,p(n)

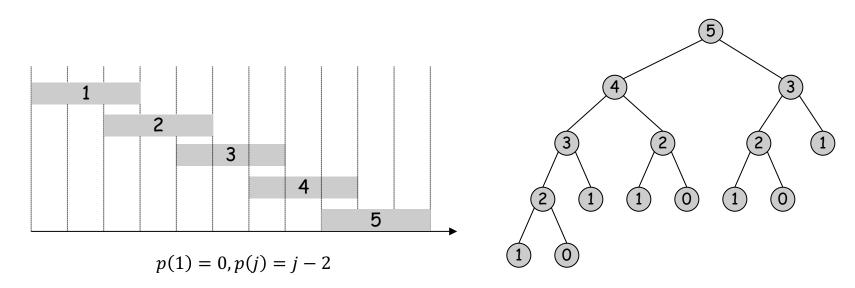
OPT(j) {
    if ( j=0 )
        return 0
    else
        return max(w_j + OPT(p(j)), OPT(j-1)).
}
```

Recursive Algorithm Fails

Even though we have only n subproblems, we do not store the solution to the subproblems

➤So, we may re-solve the same problem many many times.

Ex. Number of recursive calls for family of "layered" instances grows exponentially



Algorithm with Memoization

Memorization. Compute and Store the solution of each sub-problem in a cache the first time that you face it. lookup as needed.

```
Input: n, s(1), ..., s(n) and f(1), ..., f(n) and w_1, ..., w_n.
Sort jobs by finish times so that f(1) \le f(2) \le \cdots f(n).
Compute p(1), p(2), \dots, p(n)
for j = 1 to n
   M[j] = empty
M[0] = 0
OPT(i) {
   if (M[j] is empty)
       M[j] = max(w_j + OPT(p(j)), OPT(j-1)).
   return M[j]
}
```

Bottom up Dynamic Programming

You can also avoid recursion

recursion may be easier conceptually when you use induction

```
Input: n, s(1),...,s(n) and f(1),...,f(n) and w_1,...,w_n.

Sort jobs by finish times so that f(1) \le f(2) \le \cdots f(n). O(n log n)

Compute p(1),p(2),...,p(n) Binary search

O(n log n)

M[0] = 0

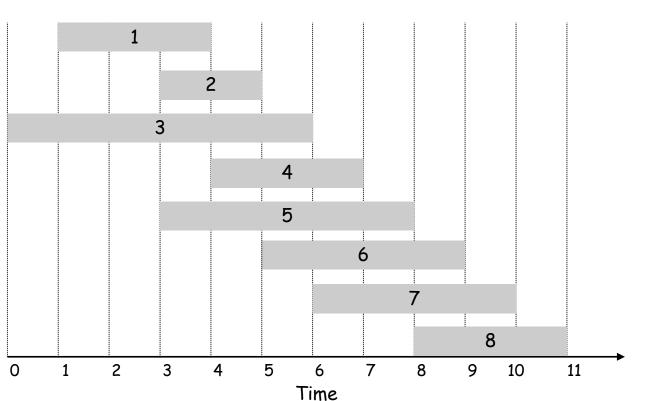
for j = 1 to n

M[j] = max(w_j + M[p(j)], M[j-1]).

O(n)
```

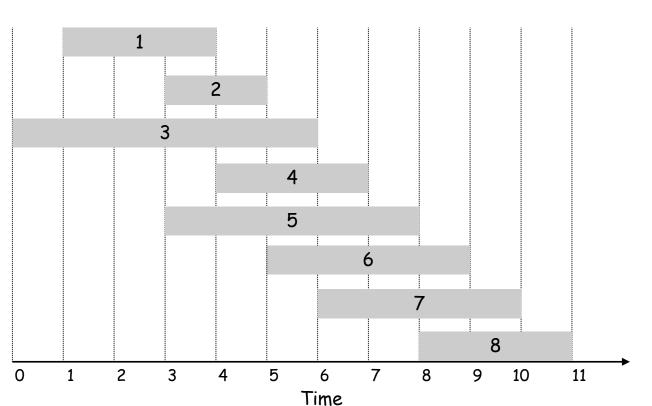
Claim: M[j] is value of OPT(j)

Example
$$OPT(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max(w_j + OPT(p(j)), OPT(j-1)) & \text{o. w.} \end{cases}$$



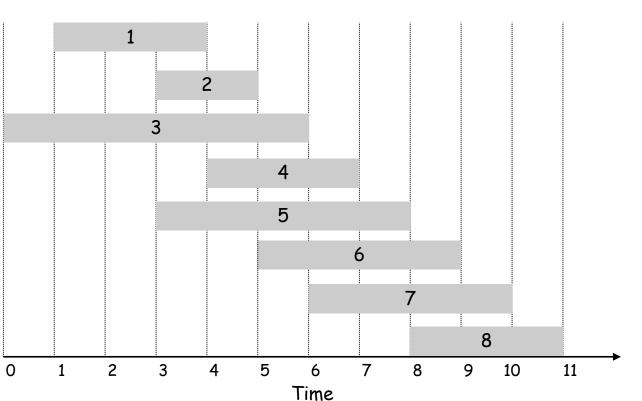
j	w_j	p(j)	OPT(j)
0			0
	3	0	
2	4	0	
3	_	0	
4	3	_	
5	4	0	
6	3	2	
7	2	3	
8	4	5	

Example
$$OPT(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max(w_j + OPT(p(j)), OPT(j-1)) & \text{o. w.} \end{cases}$$



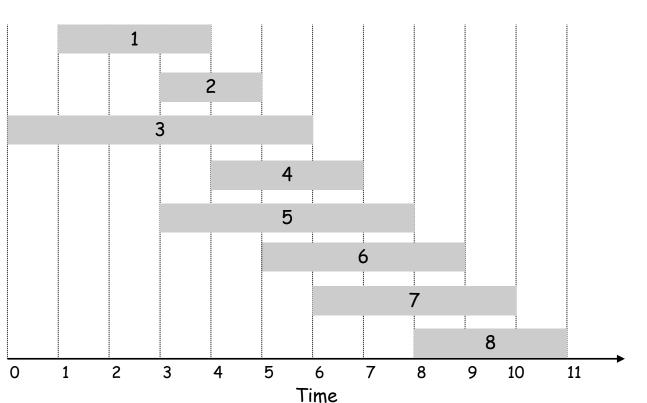
j	w_j	p(j)	OPT(j)
0			0
-	3	0	3
2	4	0	
3	-1	0	
4	3	ı	
5	4	0	
6	3	2	
7	2	3	
8	4	5	

Example
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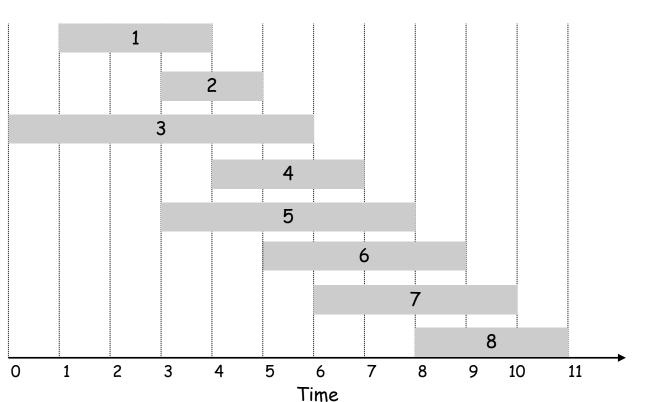
j	w_j	p(j)	OPT(j)
0			0
1	3	0	3
2	4	0	4
3	_	0	
4	3	_	
5	4	0	
6	3	2	
7	2	3	
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Example
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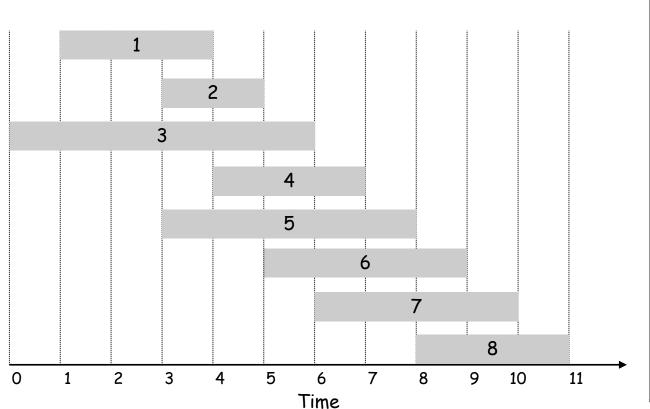
j	w_j	p(j)	OPT(j)
0			0
	3	0	3
2	4	0	4
3	1	0	4
4	3	_	
5	4	0	
6	3	2	
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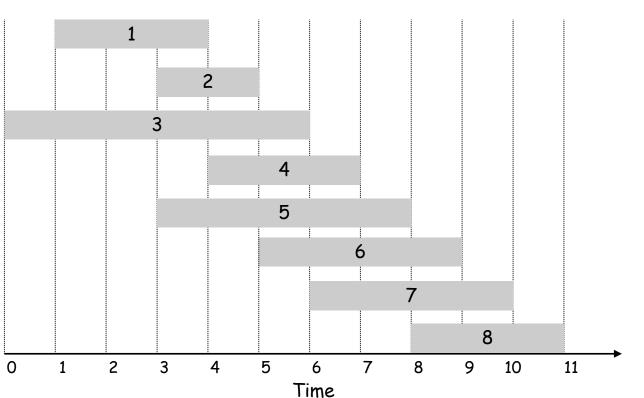
j	w_j	p(j)	OPT(j)
0			0
	3	0	3
2	4	0	4
3	1	0	4
4	3	_	6
5	4	0	
6	3	2	
7	2	3	
8	4	5	

Example
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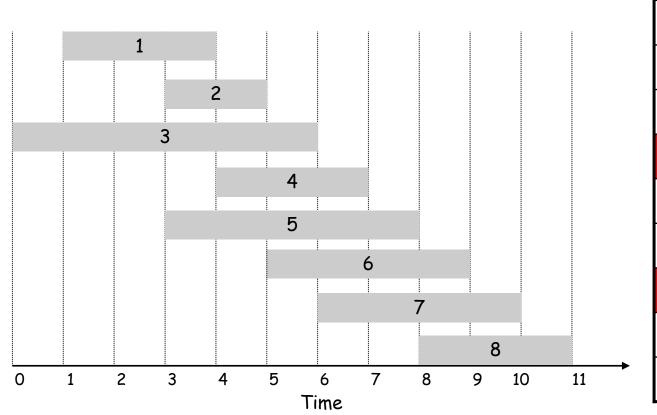
;	w_j	p(j)	OPT(j)
0			0
_	3	0	3
2	4	0	4
3	1	0	4
4	3	-1	6
5	4	0	6
6	3	2	
7	2	3	
8	4	5	

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$$OPT(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max(w_j + OPT(p(j)), OPT(j-1)) & \text{o. w.} \end{cases}$$



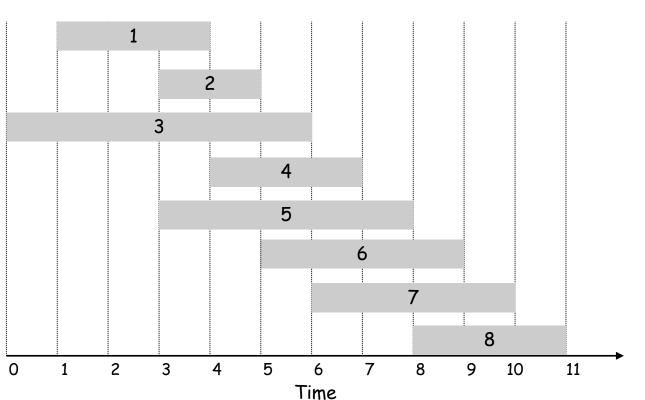
j	w_j	p(j)	OPT(j)
0			0
1	3	0	3
2	4	0	4
3	_	0	4
4	3	_	6
5	4	0	6
6	3	2	7
7	2	3	
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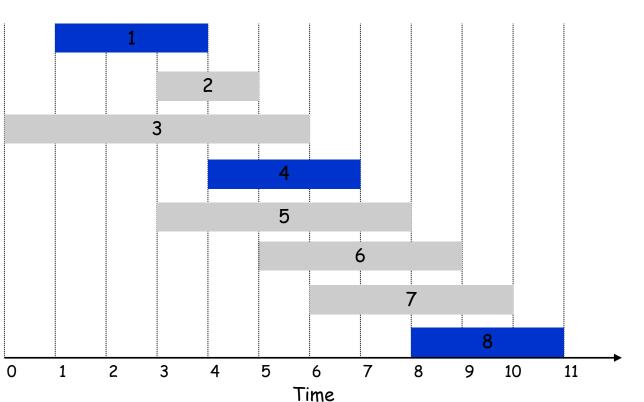
j	w_j	p(j)	OPT(j)
0			0
_	3	0	3
2	4	0	4
3	_	0	4
4	3	_	6
5	4	0	6
6	3	2	7
7	2	3	7
8	4	5	

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$$OPT(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max(w_j + OPT(p(j)), OPT(j-1)) & \text{o. w.} \end{cases}$$



j	w_j	p(j)	OPT(j)
0			0
1	3	0	3
2	4	0	4
3	-1	0	4
4	3	- 1	6
5	4	0	6
6	3	2	7
7	2	3	7
8	4	5	10

Example
$$OPT(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max(w_j + OPT(p(j)), OPT(j-1)) & \text{o. w.} \end{cases}$$



	ı		I
j	w_j	p(j)	OPT(j)
0			0
_	3	0	3
2	4	0	4
3	I	0	4
4	3	- 1	6
5	4	0	6
6	3	2	7
7	2	3	7
8	4	5	10

Dynamic Programming

 Optimal substructure: Optimal solution of a problem can be obtained from optimal solutions of smaller (overlapping) sub-problems

 Useful when the same subproblems show up again and again in the solution.