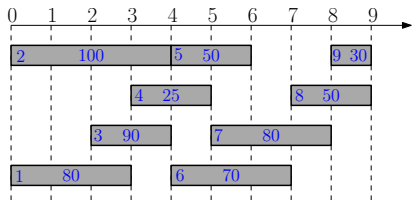


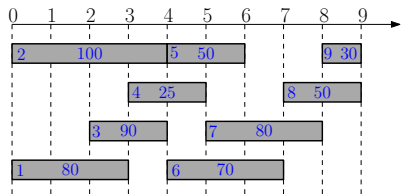
Designing a Dynamic Programming Algorithm



- Sort jobs according to non-decreasing order of finish times
- $opt[i]$: optimal value for instance only containing jobs $\{1, 2, \dots, i\}$

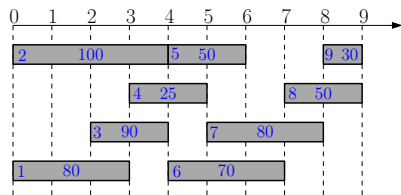
i	$opt[i]$
0	0
1	80
2	100
3	100
4	105
5	150
6	170
7	185
8	220
9	220

Designing a Dynamic Programming Algorithm



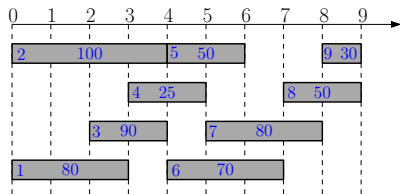
- Focus on instance $\{1, 2, 3, \dots, i\}$,
- $opt[i]$: optimal value for the instance

Designing a Dynamic Programming Algorithm



- Focus on instance $\{1, 2, 3, \dots, i\}$,
- $opt[i]$: optimal value for the instance
- assume we have computed $opt[0], opt[1], \dots, opt[i - 1]$

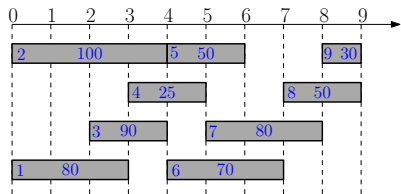
Designing a Dynamic Programming Algorithm



- Focus on instance $\{1, 2, 3, \dots, i\}$,
- $opt[i]$: optimal value for the instance
- assume we have computed $opt[0], opt[1], \dots, opt[i - 1]$

Q: The value of optimal solution that **does not contain** i ?

Designing a Dynamic Programming Algorithm

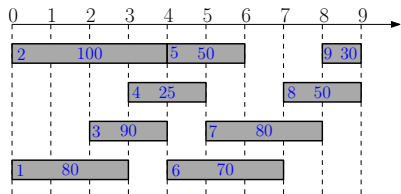


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Q: The value of optimal solution that **does not contain** i ?

A: $opt[i - 1]$

Designing a Dynamic Programming Algorithm



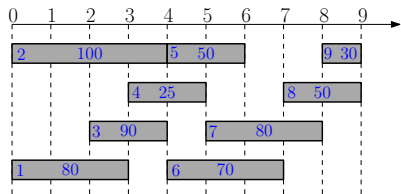
- Focus on instance $\{1, 2, 3, \dots, i\}$,
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- assume we have computed $opt[0], opt[1], \dots, opt[i - 1]$

Q: The value of optimal solution that **does not contain** i ?

A: $opt[i - 1]$

Q: The value of optimal solution that **contains** job i ?

Designing a Dynamic Programming Algorithm



- Focus on instance $\{1, 2, 3, \dots, i\}$,
- $opt[i]$: optimal value for the instance
- assume we have computed $opt[0], opt[1], \dots, opt[i - 1]$

Q: The value of optimal solution that **does not contain** i ?

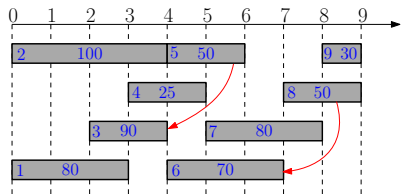
A: $opt[i - 1]$

Q: The value of optimal solution that **contains** job i ?

A: $v_i + opt[p_i]$,

$p_i =$ the largest j such that $f_j \leq s_i$

Designing a Dynamic Programming Algorithm



- Focus on instance $\{1, 2, 3, \dots, i\}$,
- $opt[i]$: optimal value for the instance
- assume we have computed $opt[0], opt[1], \dots, opt[i - 1]$

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Designing a Dynamic Programming Algorithm

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Designing a Dynamic Programming Algorithm

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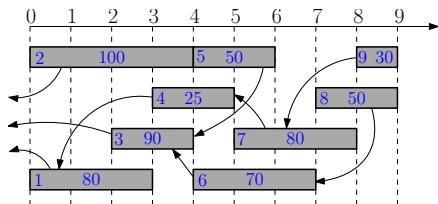
Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

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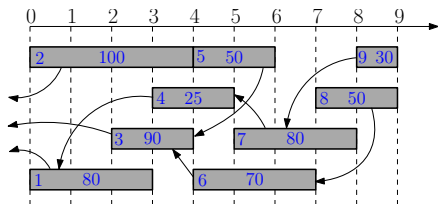


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
- $opt[2] =$
- $opt[3] =$
- $opt[4] =$
- $opt[5] =$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

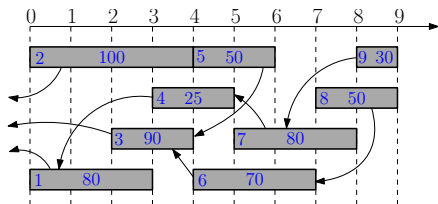


- $opt[0] = 0$
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- $opt[5] =$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

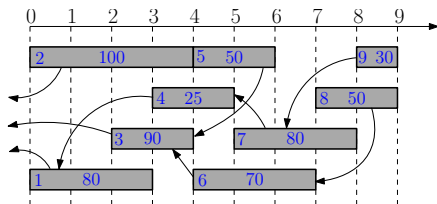


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
- $opt[2] = \max\{opt[1], 100 + opt[0]\}$
- $opt[3] =$
- $opt[4] =$
- $opt[5] =$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

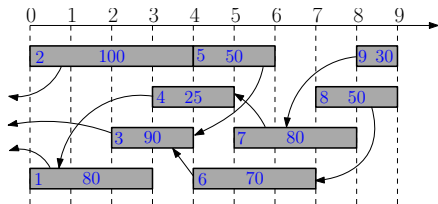


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
- $opt[2] = \max\{opt[1], 100 + opt[0]\} = 100$
- $opt[3] =$
- $opt[4] =$
- $opt[5] =$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

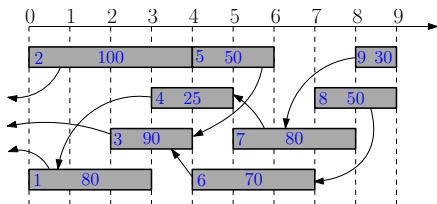


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
- $opt[2] = \max\{opt[1], 100 + opt[0]\} = 100$
- $opt[3] = \max\{opt[2], 90 + opt[0]\}$
- $opt[4] =$
- $opt[5] =$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

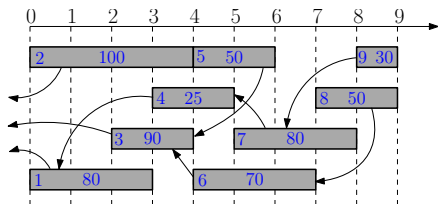


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- $opt[4] =$
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Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

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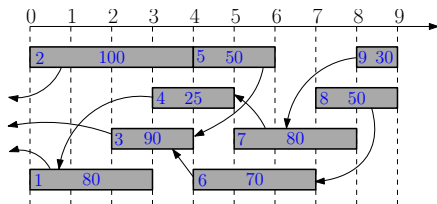


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
- $opt[2] = \max\{opt[1], 100 + opt[0]\} = 100$
- $opt[3] = \max\{opt[2], 90 + opt[0]\} = 100$
- $opt[4] = \max\{opt[3], 25 + opt[1]\}$
- $opt[5] =$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

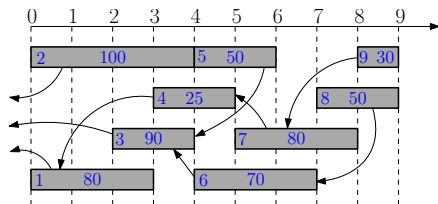


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
- $opt[2] = \max\{opt[1], 100 + opt[0]\} = 100$
- $opt[3] = \max\{opt[2], 90 + opt[0]\} = 100$
- $opt[4] = \max\{opt[3], 25 + opt[1]\} = 105$
- $opt[5] =$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

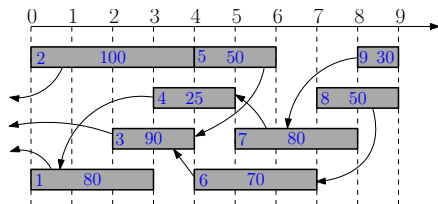


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- $opt[2] = \max\{opt[1], 100 + opt[0]\} = 100$
- $opt[3] = \max\{opt[2], 90 + opt[0]\} = 100$
- $opt[4] = \max\{opt[3], 25 + opt[1]\} = 105$
- $opt[5] = \max\{opt[4], 50 + opt[3]\}$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

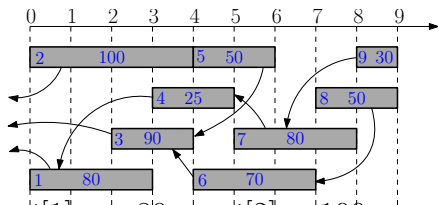


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
- $opt[2] = \max\{opt[1], 100 + opt[0]\} = 100$
- $opt[3] = \max\{opt[2], 90 + opt[0]\} = 100$
- $opt[4] = \max\{opt[3], 25 + opt[1]\} = 105$
- $opt[5] = \max\{opt[4], 50 + opt[3]\} = 150$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

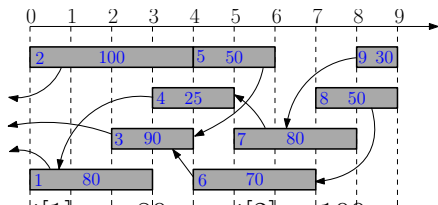


- $opt[0] = 0$, $opt[1] = 80$, $opt[2] = 100$
- $opt[3] = 100$, $opt[4] = 105$, $opt[5] = 150$

Designing a Dynamic Programming Algorithm

Recursion for $opt[i]$:

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$



- $opt[0] = 0$, $opt[1] = 80$, $opt[2] = 100$
- $opt[3] = 100$, $opt[4] = 105$, $opt[5] = 150$
- $opt[6] = \max\{opt[5], 70 + opt[3]\} = 170$
- $opt[7] = \max\{opt[6], 80 + opt[4]\} = 185$
- $opt[8] = \max\{opt[7], 50 + opt[6]\} = 220$
- $opt[9] = \max\{opt[8], 30 + opt[7]\} = 220$

Dynamic Programming

- 1: sort jobs by non-decreasing order of finishing times
- 2: compute p_1, p_2, \dots, p_n
- 3: $opt[0] \leftarrow 0$
- 4: **for** $i \leftarrow 1$ to n **do**
- 5: $opt[i] \leftarrow \max\{opt[i - 1], v_i + opt[p_i]\}$

Dynamic Programming

- 1: sort jobs by non-decreasing order of finishing times
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- 5: $opt[i] \leftarrow \max\{opt[i - 1], v_i + opt[p_i]\}$

- Running time sorting: $O(n \lg n)$
- Running time for computing p : $O(n \lg n)$ via binary search
- Running time for computing $opt[n]$: $O(n)$

How Can We Recover the Optimum Schedule?

```
1: sort jobs by non-decreasing order of
   finishing times
2: compute  $p_1, p_2, \dots, p_n$ 
3:  $opt[0] \leftarrow 0$ 
4: for  $i \leftarrow 1$  to  $n$  do
5:     if  $opt[i - 1] \geq v_i + opt[p_i]$  then
6:          $opt[i] \leftarrow opt[i - 1]$ 
7:
8:     else
9:          $opt[i] \leftarrow v_i + opt[p_i]$ 
10:
```

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3:  $opt[0] \leftarrow 0$ 
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5:     if  $opt[i - 1] \geq v_i + opt[p_i]$  then
6:          $opt[i] \leftarrow opt[i - 1]$ 
7:          $b[i] \leftarrow N$ 
8:     else
9:          $opt[i] \leftarrow v_i + opt[p_i]$ 
10:         $b[i] \leftarrow Y$ 
```

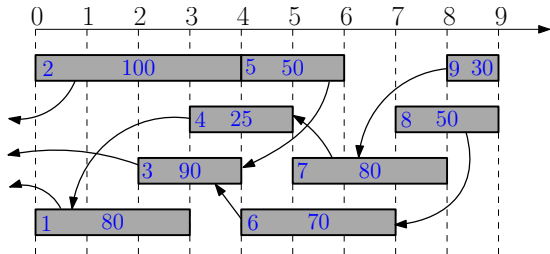
How Can We Recover the Optimum Schedule?

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7:          $b[i] \leftarrow N$ 
8:     else
9:          $opt[i] \leftarrow v_i + opt[p_i]$ 
10:         $b[i] \leftarrow Y$ 
```

```
1:  $i \leftarrow n, S \leftarrow \emptyset$ 
2: while  $i \neq 0$  do
3:     if  $b[i] = N$  then
4:          $i \leftarrow i - 1$ 
5:     else
6:          $S \leftarrow S \cup \{i\}$ 
7:          $i \leftarrow p_i$ 
8: return  $S$ 
```

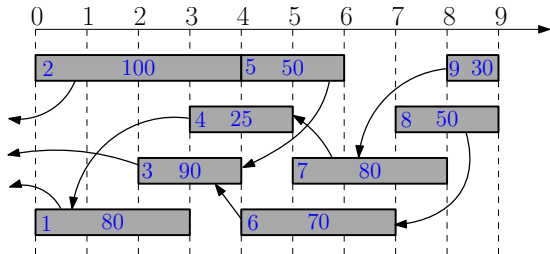
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	
2	100	
3	100	
4	105	
5	150	
6	170	
7	185	
8	220	
9	220	



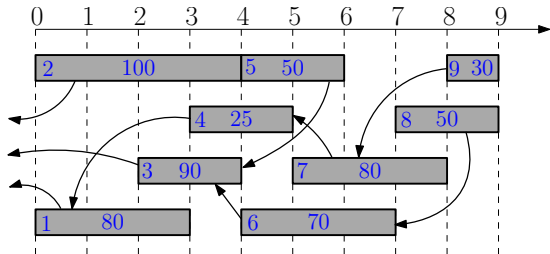
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1	80	Y
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3	100	
4	105	
5	150	
6	170	
7	185	
8	220	
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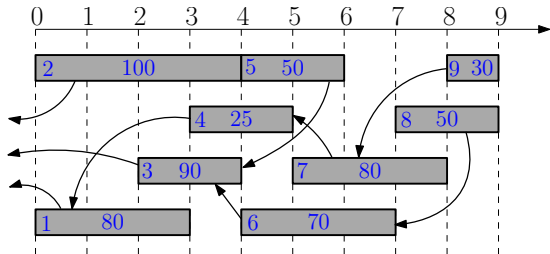
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4	105	
5	150	
6	170	
7	185	
8	220	
9	220	



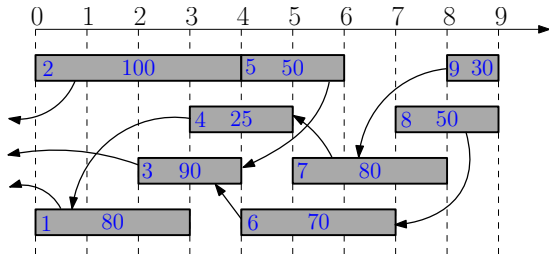
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	
5	150	
6	170	
7	185	
8	220	
9	220	



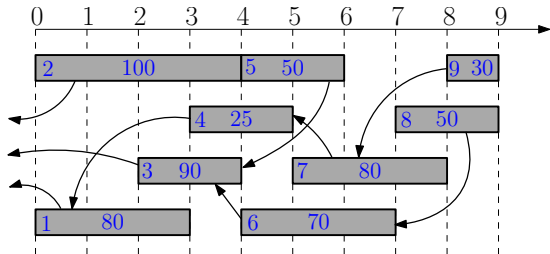
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	
6	170	
7	185	
8	220	
9	220	



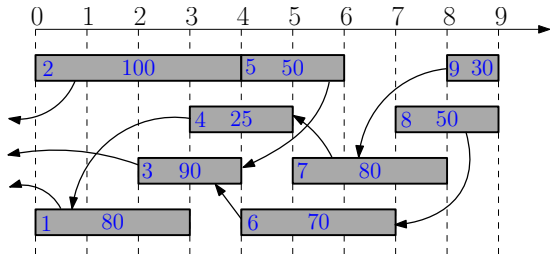
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	
7	185	
8	220	
9	220	



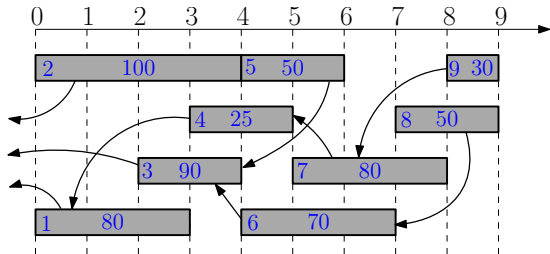
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	
8	220	
9	220	



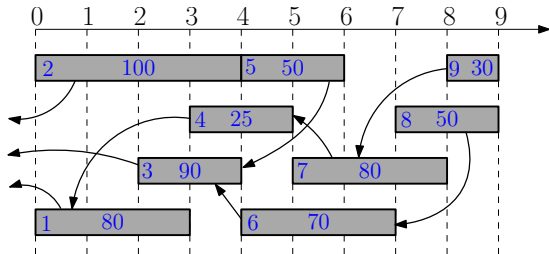
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	
9	220	



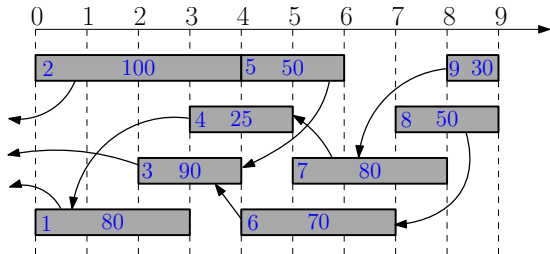
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i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	



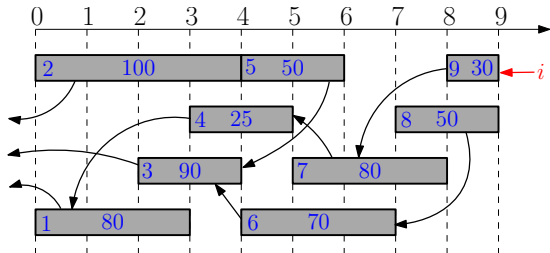
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	N



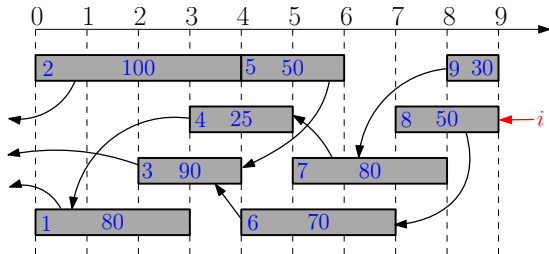
Recovering Optimum Schedule: Example

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0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	N



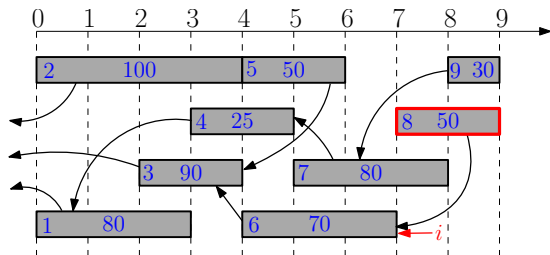
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	N



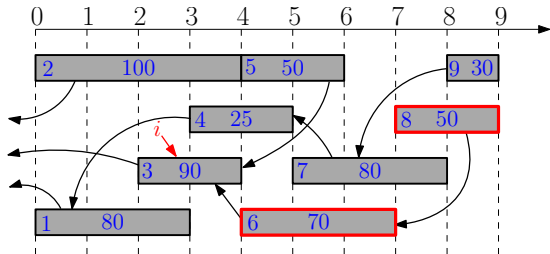
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i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	N



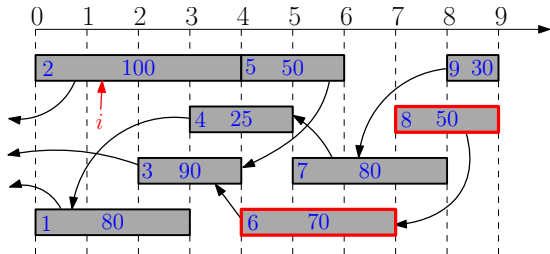
Recovering Optimum Schedule: Example

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0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	N



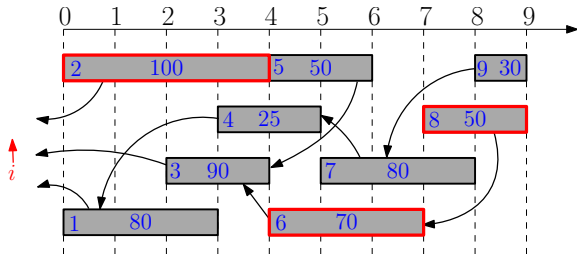
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1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	N



Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	Y
2	100	Y
3	100	N
4	105	Y
5	150	Y
6	170	Y
7	185	Y
8	220	Y
9	220	N



Dynamic Programming

- Break up a problem into many **overlapping** sub-problems
- Build solutions for larger and larger sub-problems
- Use a **table** to store solutions for sub-problems for reuse

Outline

- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem**
- 3 Knapsack Problem
- 4 Longest Common Subsequence
 - Longest Common Subsequence in Linear Space
- 5 Shortest Paths in Directed Acyclic Graphs
- 6 Matrix Chain Multiplication
- 7 Optimum Binary Search Tree
- 8 Summary

Subset Sum Problem

Input: an integer bound $W > 0$

a set of n items, each with an integer weight $w_i > 0$

Output: a subset S of items that

$$\text{maximizes } \sum_{i \in S} w_i \quad \text{s.t. } \sum_{i \in S} w_i \leq W.$$

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- $W = 35, n = 5, w = (14, 9, 17, 10, 13)$

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Example:

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- Optimum: $S = \{1, 2, 4\}$ and $14 + 9 + 10 = 33$

Greedy Algorithms for Subset Sum

Candidate Algorithm:

- Sort according to non-increasing order of weights
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Design a Dynamic Programming Algorithm

- Consider the instance: $i, W', (w_1, w_2, \dots, w_i)$;
- $opt[i, W']$: the optimum value of the instance

Q: The value of the optimum solution that **does not contain** i ?

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A: $opt[i - 1, W' - w_i] + w_i$

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$$opt[i, W'] = \begin{cases} i = 0 \\ i > 0, w_i > W' \\ i > 0, w_i \leq W' \end{cases}$$

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$$opt[i, W'] = \begin{cases} 0 & i = 0 \\ opt[i - 1, W'] & i > 0, w_i > W' \\ \max \left\{ \begin{array}{l} opt[i - 1, W'] \\ opt[i - 1, W' - w_i] + w_i \end{array} \right\} & i > 0, w_i \leq W' \end{cases}$$