

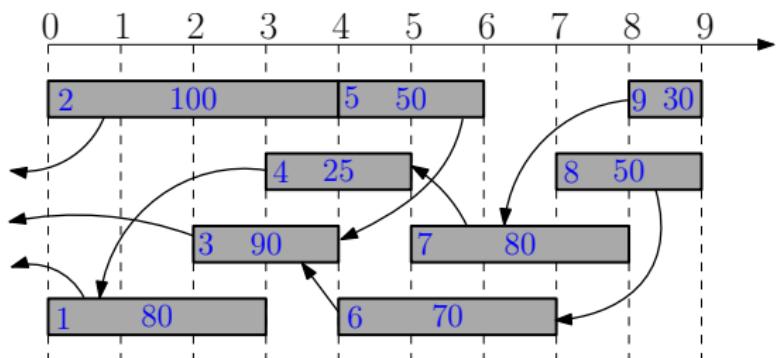
How Can We Recover the Optimum Schedule?

```
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:      $b[i] \leftarrow N$   
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  $S$ 
```

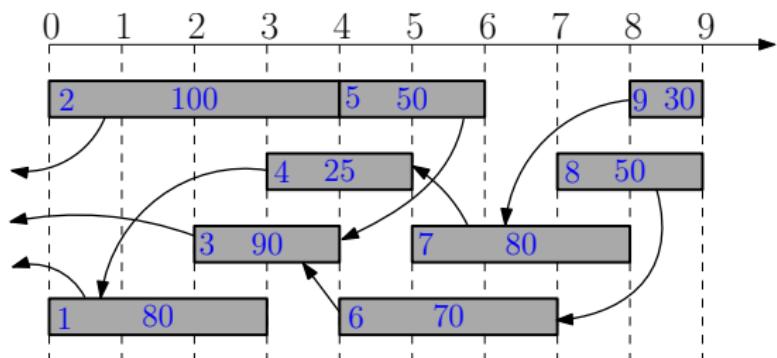
Recovering Optimum Schedule: Example

i	$opt[i]$	$b[i]$
0	0	\perp
1	80	
2	100	
3	100	
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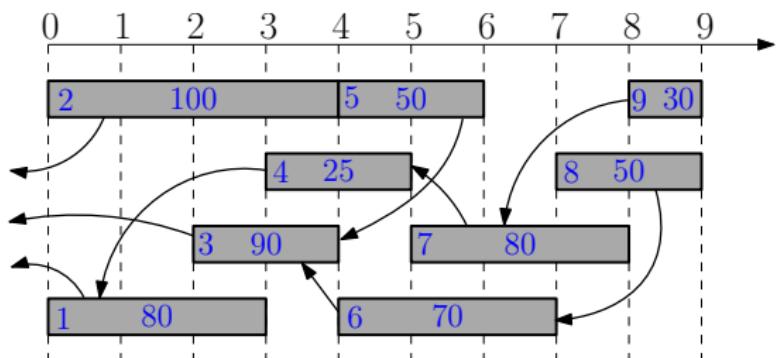
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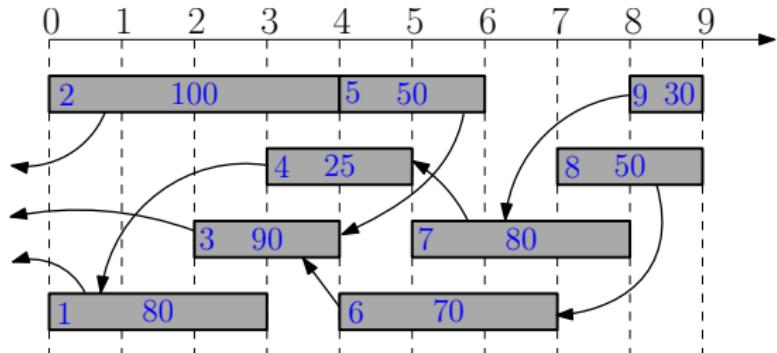
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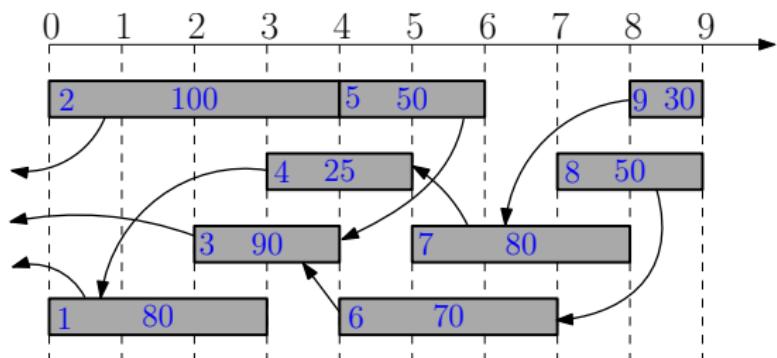
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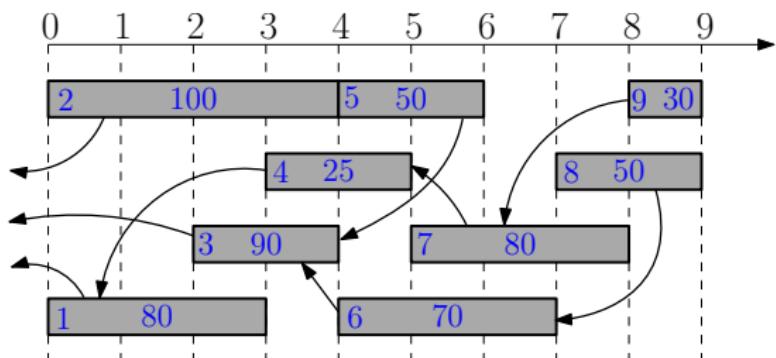
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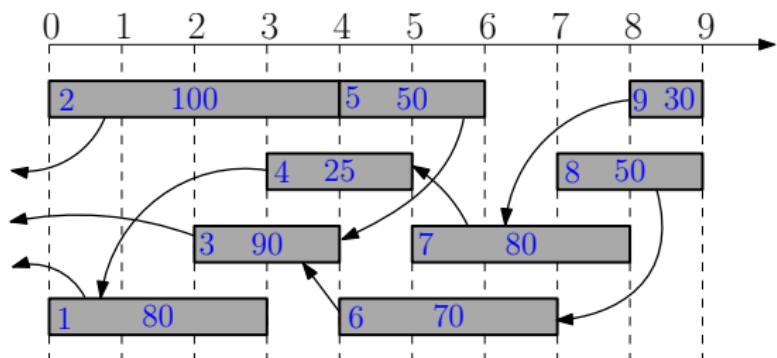
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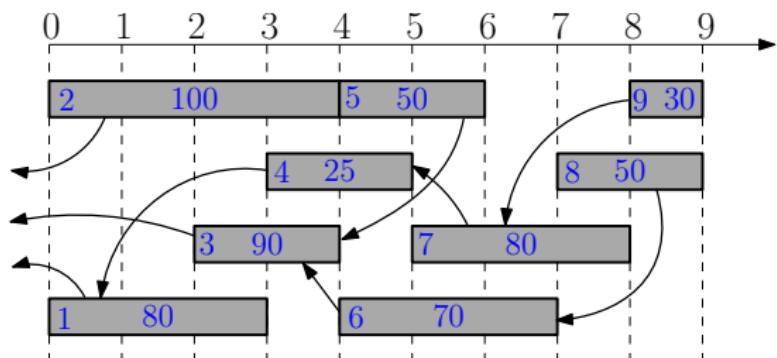
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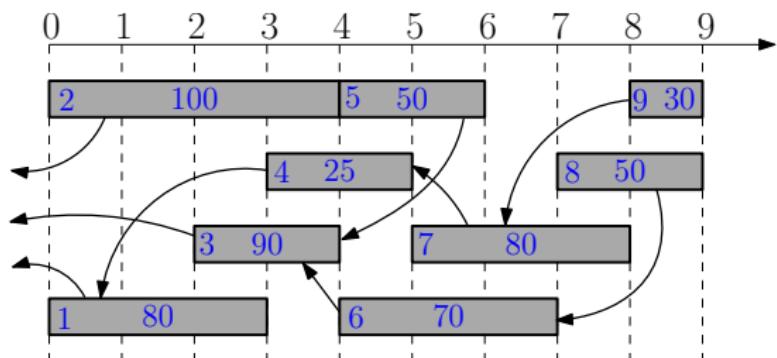
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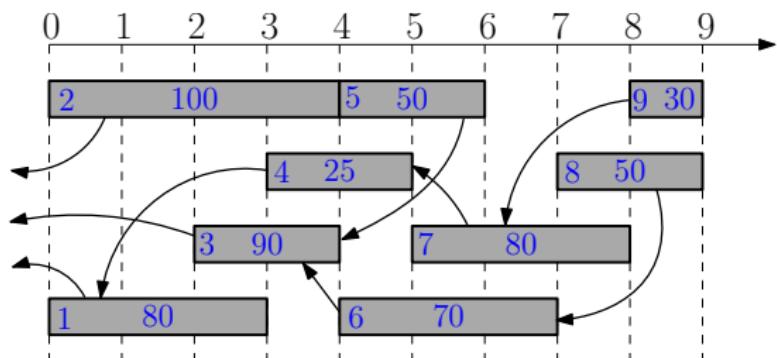
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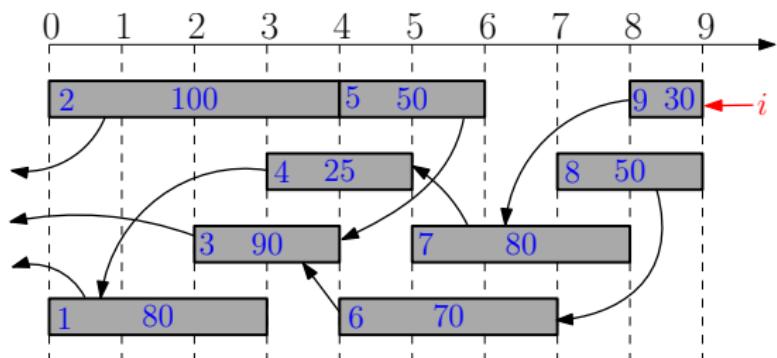
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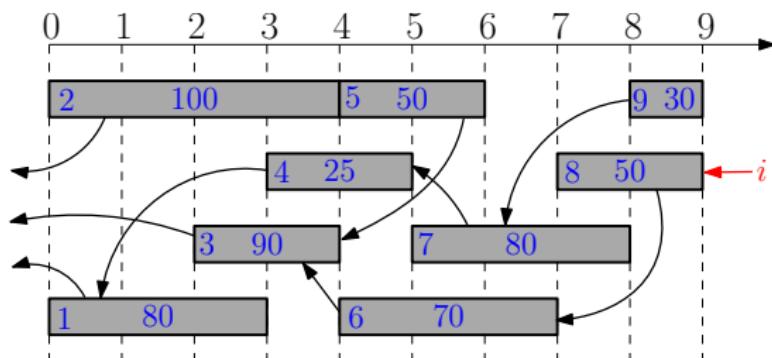
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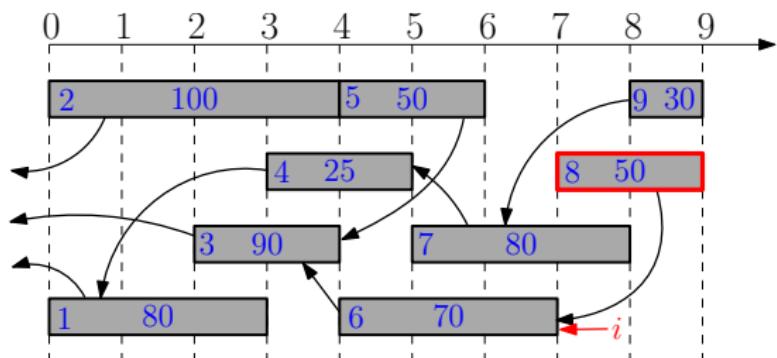
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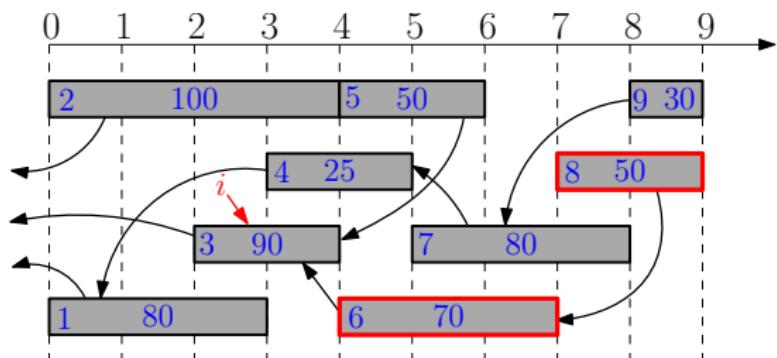
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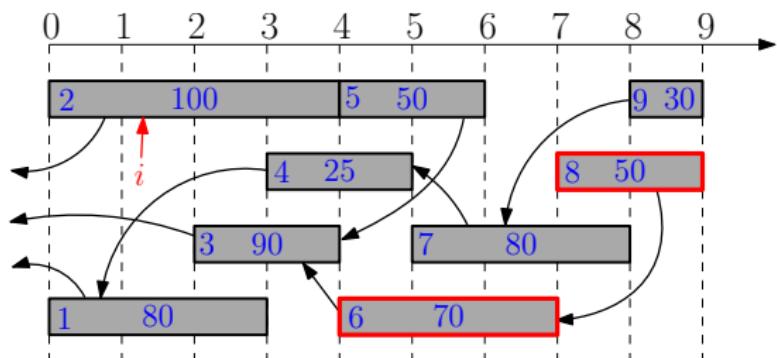
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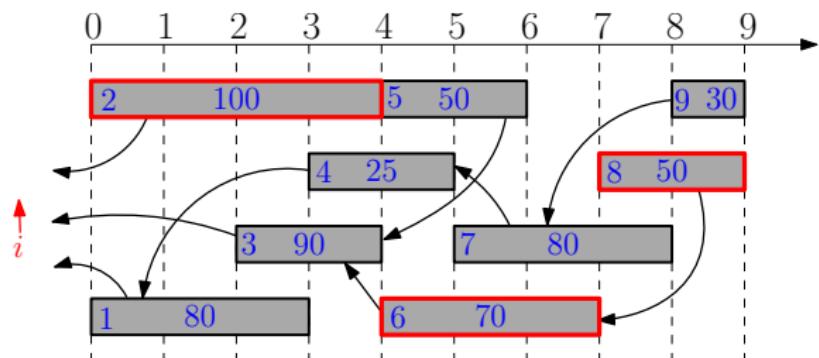
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Dynamic Programming

- 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
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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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- Motivation: you have budget W , and want to buy a subset of items, so as to spend as much money as possible.

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Example:

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

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Example:

- $W = 35, n = 5, w = (14, 9, 17, 10, 13)$
- 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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A: No. $W = 100, n = 3, w = (51, 50, 50)$.

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

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

Q: The value of the optimum solution that **contains** i ?

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

Dynamic Programming

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

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

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Dynamic Programming

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

Dynamic Programming

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1: for  $W' \leftarrow 0$  to  $W$  do
2:    $opt[0, W'] \leftarrow 0$ 
3: for  $i \leftarrow 1$  to  $n$  do
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8: return  $opt[n, W]$ 
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Recover the Optimum Set

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then
8:        $opt[i, W'] \leftarrow opt[i - 1, W' - w_i] + w_i$ 
9:        $b[i, W'] \leftarrow Y$ 
10: return  $opt[n, W]$ 
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Recover the Optimum Set

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1:  $i \leftarrow n, W' \leftarrow W, S \leftarrow \emptyset$ 
2: while  $i > 0$  do
3:   if  $b[i, W'] = Y$  then
4:      $W' \leftarrow W' - w_i$ 
5:      $S \leftarrow S \cup \{i\}$ 
6:    $i \leftarrow i - 1$ 
7: return  $S$ 
```

Running Time of Algorithm

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1: for  $W' \leftarrow 0$  to  $W$  do
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- Running time is $O(nW)$

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- Running time is **pseudo-polynomial** because it depends on value of the input integers.

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- Game's running time:
<https://courses.csail.mit.edu/6.5440/fall23/>

Avoiding Unnecessary Computation and Memory Using Memoized Algorithm and Hash Map

compute-opt(i, W')

```
1: if  $opt[i, W'] \neq \perp$  then return  $opt[i, W']$ 
2: if  $i = 0$  then  $r \leftarrow 0$ 
3: else
4:    $r \leftarrow \text{compute-opt}(i - 1, W')$ 
5:   if  $w_i \leq W'$  then
6:      $r' \leftarrow \text{compute-opt}(i - 1, W' - w_i) + w_i$ 
7:     if  $r' > r$  then  $r \leftarrow r'$ 
8:    $opt[i, W'] \leftarrow r$ 
9: return  $r$ 
```

- Use hash map for opt

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Knapsack Problem

Input: an integer bound $W > 0$

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

a value $v_i > 0$ for each item i

Output: a subset S of items that

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