
Dynamic Programming

Dynamic Programming (DP)

- An algorithm design technique (like divide and conquer)
- Divide and conquer
 - Partition the problem into independent subproblems
 - Solve the subproblems recursively
 - Combine the solutions to solve the original problem

DP vs. Divide and Conquer

- DP applies when the subproblems overlap—that is, when subproblems share subsubproblems.
- A divide-and-conquer algorithm does more work than necessary, repeatedly solving the common subsubproblems.
- A DP algorithm solves each subsubproblem just once and then saves its answer in a table, thereby avoiding the work of recomputing the answer every time it solves each subsubproblem

More about DP

- We typically apply dynamic programming to optimization problems. Such problems can have many possible solutions. Each solution has a value, and we wish to find a solution with the optimal (minimum or maximum) value. We call such a solution an optimal solution to the problem, as opposed to the optimal solution, since there may be several solutions that achieve the optimal value

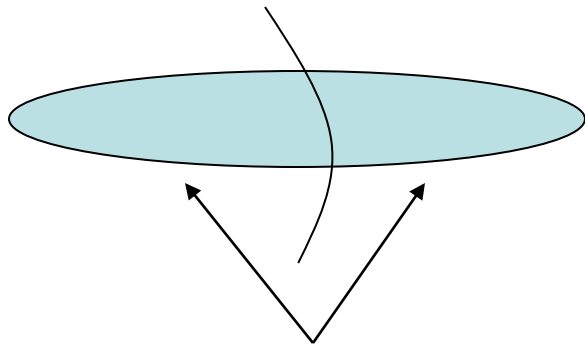
Steps taken in DP

- When developing a dynamic-programming algorithm, we follow a sequence of four steps:
 - Characterize the structure of an optimal solution.
 - Recursively define the value of an optimal solution.
 - Compute the value of an optimal solution, typically in a bottom-up fashion.
 - Construct an optimal solution from computed information.

DP - Two key ingredients

- Two key ingredients for an optimization problem to be suitable for a dynamic-programming solution:

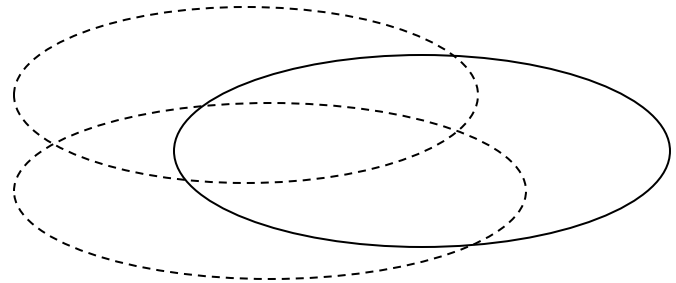
1. optimal substructures



Each substructure is optimal.

(Principle of optimality)

2. overlapping subproblems



Subproblems are dependent.

(otherwise, a divide-and-conquer approach is the choice.)

Three basic components

- The development of a dynamic-programming algorithm has three basic components:
 - The recurrence relation (for defining the value of an optimal solution);
 - The tabular computation (for computing the value of an optimal solution);
 - The traceback (for delivering an optimal solution).

Fibonacci numbers

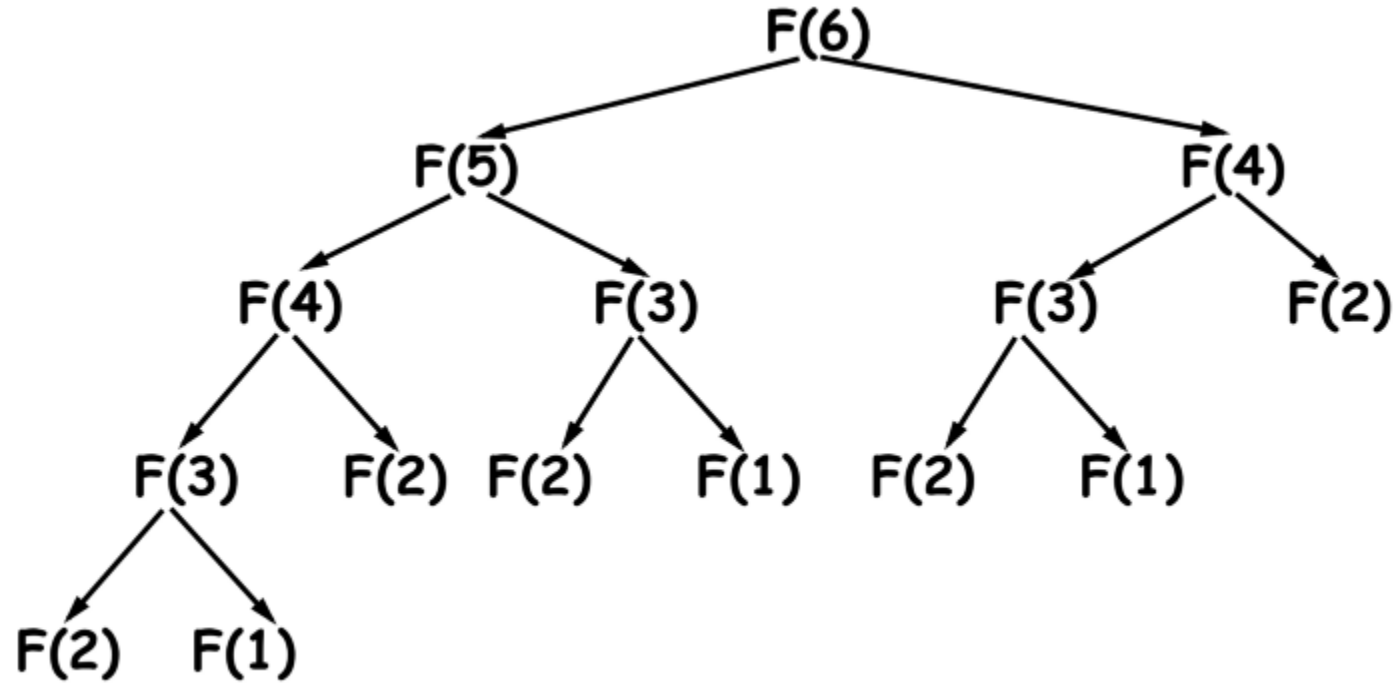
The *Fibonacci numbers* are defined by the following recurrence:

$$F_0 = 0$$

$$F_1 = 1$$

$$F_i = F_{i-1} + F_{i-2} \quad \text{for } i > 1.$$

How to compute F_{10} ?



Dynamic Programming

- Applicable when subproblems are not independent

- Subproblems share subsubproblems


E.g.: Fibonacci numbers:

- Recurrence: $F(n) = F(n-1) + F(n-2)$
- Boundary conditions: $F(1) = 0, F(2) = 1$
- Compute: $F(5) = 3, F(3) = 1, F(4) = 2$
- A divide and conquer approach would repeatedly solve the common subproblems
- Dynamic programming solves every subproblem just once and stores the answer in a table

Tabular computation

- The tabular computation can avoid recomputation.

F_0	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
0	1	1	2	3	5	8	13	21	34	55



Result

1. Solving Problems using DP

Sequences

Definition

Sequence: an ordered list a_1, a_2, \dots, a_n . **Length** of a sequence is number of elements in the list.

Definition

a_{i_1}, \dots, a_{i_k} is a **subsequence** of a_1, \dots, a_n if
 $1 \leq i_1 < \dots < i_k \leq n$.

Definition

A sequence is **increasing** if $a_1 < a_2 < \dots < a_n$. It is **non-decreasing** if $a_1 \leq a_2 \leq \dots \leq a_n$. Similarly **decreasing** and **non-increasing**.

Sequences

Example...

Example

- Sequence: 6, 3, 5, 2, 7, 8, 1
- Subsequence: 5, 2, 1
- Increasing sequence: 3, 5, 9
- Increasing subsequence: 2, 7, 8

Longest increasing subsequence(LIS)

- The longest increasing subsequence is to find a longest increasing subsequence of a given sequence of distinct integers $a_1 a_2 \dots a_n$.

e.g. 9 2 5 3 7 11 8 10 13 6

2 3 7

5 7 10 13

9 7 11

3 5 11 13

} are increasing subsequences.

We want to find a longest one.

} are not increasing subsequences.

Longest Increasing Subsequence Problem

Input A sequence of numbers a_1, a_2, \dots, a_n

Goal Find an *increasing subsequence* $a_{i_1}, a_{i_2}, \dots, a_{i_k}$ of maximum length

Example

- Sequence: 6, 3, 5, 2, 7, 8, 1
- Increasing subsequences: 6, 7, 8 and 3, 5, 7, 8 and 2, 7 etc
- Longest increasing subsequence: 3, 5, 7, 8

A naive approach for LIS

Assume a_1, a_2, \dots, a_n is contained in an array A

```
algLISNaive(A[1..n]):  
    max = 0  
    for each subsequence B of A do  
        if B is increasing and |B| > max then  
            max = |B|  
  
    Output max
```


A naive approach for LIS

Assume a_1, a_2, \dots, a_n is contained in an array A

```
algLISNaive(A[1..n]):  
    max = 0  
    for each subsequence B of A do  
        if B is increasing and  $|B| > \text{max}$  then  
            max =  $|B|$   
  
    Output max
```

Running time: $O(n2^n)$.

2^n subsequences of a sequence of length n and $O(n)$ time to check if a given sequence is increasing.

A naive approach for LIS

- Let **L[i]** be the length of a longest increasing subsequence ending at position *i*.

$$L[i] = 1 + \max_{j = 0..i-1} \{L[j] \mid a_j < a_i\}$$

(use a dummy $a_0 = \text{minimum}$, and $L[0]=0$)

Index	0	1	2	3	4	5	6	7	8	9	10
Input	0	9	2	5	3	7	11	8	10	13	6
Length	0	1	1	2	2	3	4	4	5	6	3
Prev	-1	0	0	2	2	4	5	5	7	8	4
Path	1	1	1	1	1	2	2	2	2	2	2

The subsequence 2, 3, 7, 8, 10, 13 is a longest increasing subsequence.

This method runs in $O(n^2)$ time.

Algorithm

Simplifying:

```
LIS(A[1..n]):  
    Array L[1..n]  
        (* L[i] stores the value LIS-Ending(A[1..i]) *)  
    m = 0  
    for i = 1 to n do  
        L[i] = 1  
        for j = 1 to i - 1 do  
            if (A[j] < A[i]) do  
                L[i] = max(L[i], 1 + L[j])  
        m = max(m, L[i])  
    return m
```

Running time: $O(n^2)$

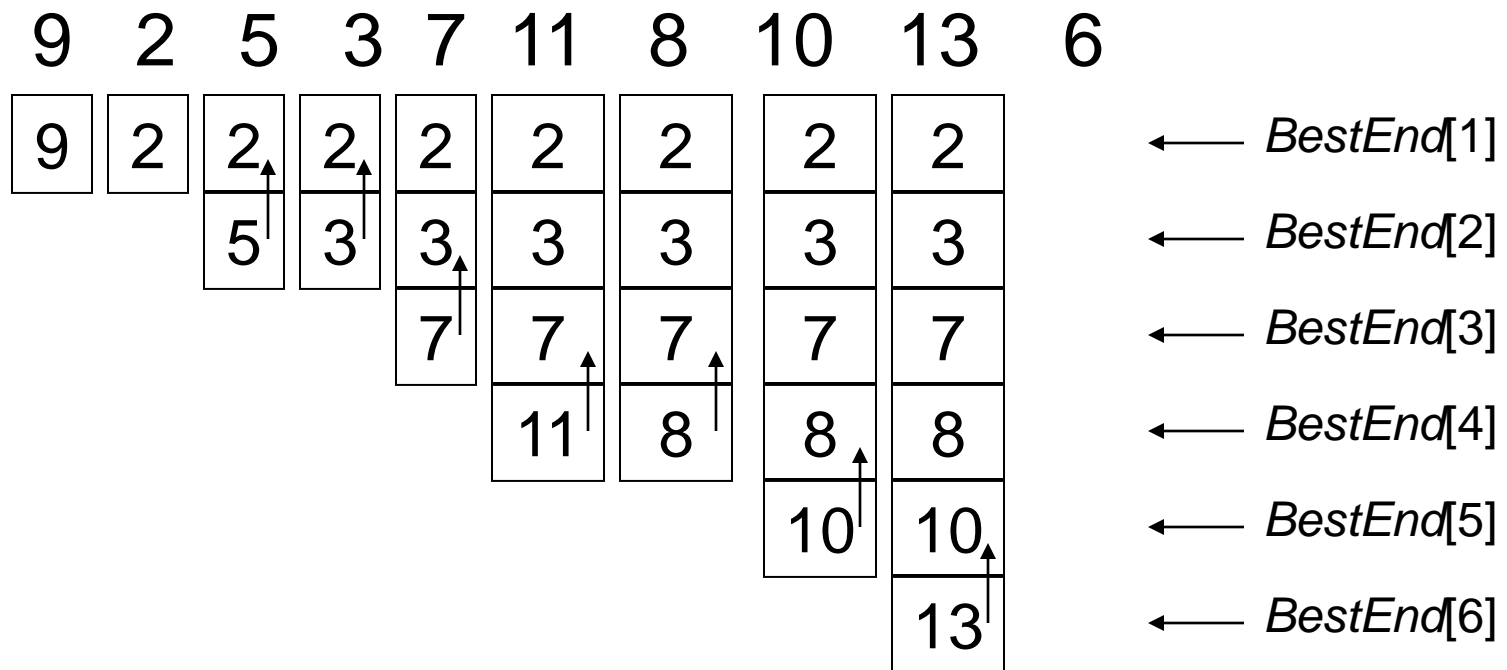
A better solution

One can compute LIS in $O(n \log n)$ time

TRY YOURSELF !!!!!!!

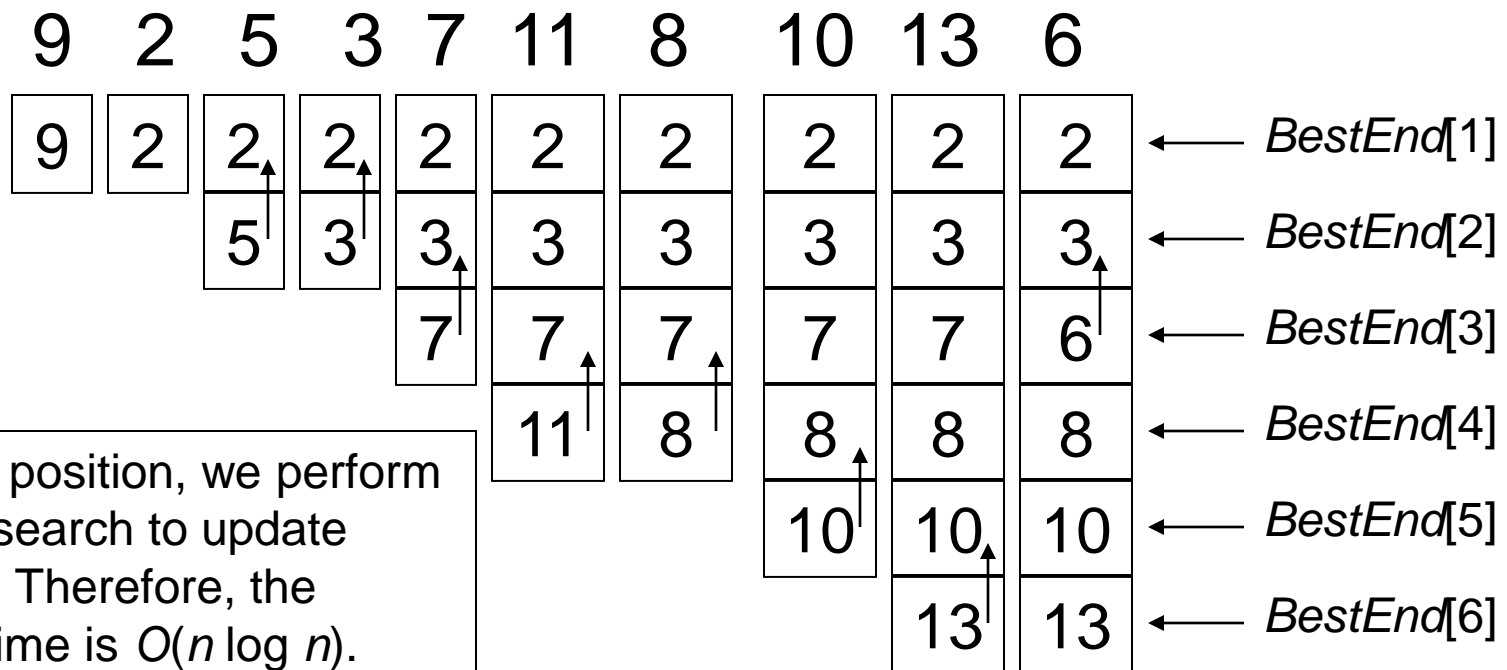
An $O(n \log n)$ method for LIS

- Define $BestEnd[k]$ to be the smallest number of an increasing subsequence of length k .



An $O(n \log n)$ method for LIS

- Define $BestEnd[k]$ to be the smallest number of an increasing subsequence of length k .



For each position, we perform a binary search to update $BestEnd$. Therefore, the running time is $O(n \log n)$.

2. Sum of Subset Problem

- Problem:

- Suppose you are given N positive integer numbers $A[1..N]$ and it is required to produce another number K using a subset of $A[1..N]$ numbers. How can it be done using Dynamic programming approach?

- Example:

$N = 6$, $A[1..N] = \{2, 5, 8, 12, 6, 14\}$, $K = 19$

Result: $2 + 5 + 12 = 19$

Algorithm

- Use a two dimensional array

			w1	w2	w3	...	ws
Input[i]		0	1	2	3	...	s
	0						
2	1						
3	2						
7	3						
	.						
	.						
10	n						

i

j

Algorithm



- for (int i = 0; i <= n; i++)
 - s[0][i] = 1;

The diagram illustrates a 2D array `s` with a vertical axis labeled `i` and a horizontal axis labeled `j`. A vertical blue arrow points downwards along the first column, and a horizontal blue arrow points to the right from the second row. The array is structured as follows:

			w1	w2	w3	...	ws
Input[i]		0	1	2	3	...	s
	0	1					
2	1	1					
3	2	1					
7	3	1					
	.	1					
	.	1					
10	n	1					

Algorithm

- for (int j = 1; j <= s; j++)
 - s[j][0] = 0;

			w1	w2	w3	...	ws	
Input[i]		0	1	2	3	...	s	
	0	1	0	0	0	0	0	
2	1	1						S
3	2	1						
7	3	1						
	.	1						
	.	1						
10	n	1						
								i

Algorithm

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

			w1	w2	w3	...	ws	
Input[i]		0	1	2	3	...	s	
	0	1	0	0	0	0	0	
2	1	1	→					j
3	2	1						
7	3	1						
	.	1						
	.	1						
10	n	1						

i

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0												
2	1												
3	2												
7	3												
8	4												
10	5												

Input={2,3,7,8,10}
S=11

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1											
3	2	1											
7	3	1											
8	4	1											
10	5	1											

Input={2,3,7,8,10}
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Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \text{ || } s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0										
3	2	1											
7	3	1											
8	4	1											
10	5	1											

Input={2,3,7,8,10}
S=11

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

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input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0										
3	2	1											
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Input={2,3,7,8,10}
S=11

(1 || 0)=1

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1									
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Example

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		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1											
7	3	1											
8	4	1											
10	5	1											

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$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \text{ || } s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0										
7	3	1											
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10	5	1											

Input={2,3,7,8,10}
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Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \text{ || } s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1									
7	3	1											
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Example

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		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1									
7	3	1											
8	4	1											
10	5	1											

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(1 || 0)=1

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1	1								
7	3	1											
8	4	1											
10	5	1											

Input={2,3,7,8,10}
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Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1	1	0	1	0	0	0	0	0	0
7	3	1											
8	4	1											
10	5	1											

Input={2,3,7,8,10}
S=11

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1	1	0	1	0	0	0	0	0	0
7	3	1	0	1	1	0	1	0	1	0	1	1	0
8	4	1	0	1	1	0	1	0	1	1	1	1	1
10	5	1	0	1	1	0	1	0	1	1	1	1	1

Input={2,3,7,8,10}
S=11

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1	1	0	1	0	0	0	0	0	0
7	3	1	0	1	1	0	1	0	1	0	1	1	0
8	4	1	0	1	1	0	1	0	1	1	1	1	1
10	5	1	0	1	1	0	1	0	1	1	1	1	1

Input={2,3,7,8,10}
S=11

8,10

Example

$$s[i, j] = \begin{cases} s[i-1, j] & \text{if } j < \text{input}[i] \\ s[i-1, j] \parallel s[i-1, j - \text{input}[i]] & \text{otherwise} \end{cases}$$

		0	1	2	3	4	5	6	7	8	9	10	11
input	0	1	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0
3	2	1	0	1	1	0	1	0	0	0	0	0	0
7	3	1	0	1	1	0	1	0	1	0	1	1	0
8	4	1	0	1	1	0	1	0	1	1	1	1	1
10	5	1	0	1	1	0	1	0	1	1	1	1	1

Input={2,3,7,8,10}
S=11

2,3, 8,10

Algorithm

```
for (int i = 0; i <= n; i++)
    s[0][i] = 1;
for (int j = 1; j <= s; j++)
    s[j][0] = 0;
for (int i = 1; i <= n; i++)
    for (int j = 1; j <= s; j++)
    {
        if(j<input[i])
            s[i][j]=s[i][j-1]
        else
            s[i][j]=s[i][j-1] || s[i][j-input[i]]
    }
```

Coin Change Problem

- Suppose you are given n types of coin - C_1, C_2, \dots, C_n coin, and another number K .
- Is it possible to make K using above types of coin?
 - Number of each coin is infinite
 - Number of each coin is finite
- Find minimum number of coin that is required to make K ?
 - Number of each coin is infinite
 - Number of each coin is finite

Maximum-sum interval

- Given a sequence of real numbers $a_1 a_2 \dots a_n$, find a consecutive subsequence with the maximum sum.

9 -3 1 7 -15 2 3 -4 2 -7 6 -2 8 4 -9

For each position, we can compute the maximum-sum interval starting at that position in $O(n)$ time. Therefore, a naive algorithm runs in $O(n^2)$ time.

Try Yourself

The Knapsack Problem

- **The 0-1 knapsack problem**

- A thief robbing a store finds n items: the i -th item is worth v_i dollars and weights w_i pounds (v_i, w_i integers)
- The thief can only carry W pounds in his knapsack
- Items must be taken entirely or left behind
- Which items should the thief take to maximize the value of his load?

- **The fractional knapsack problem**

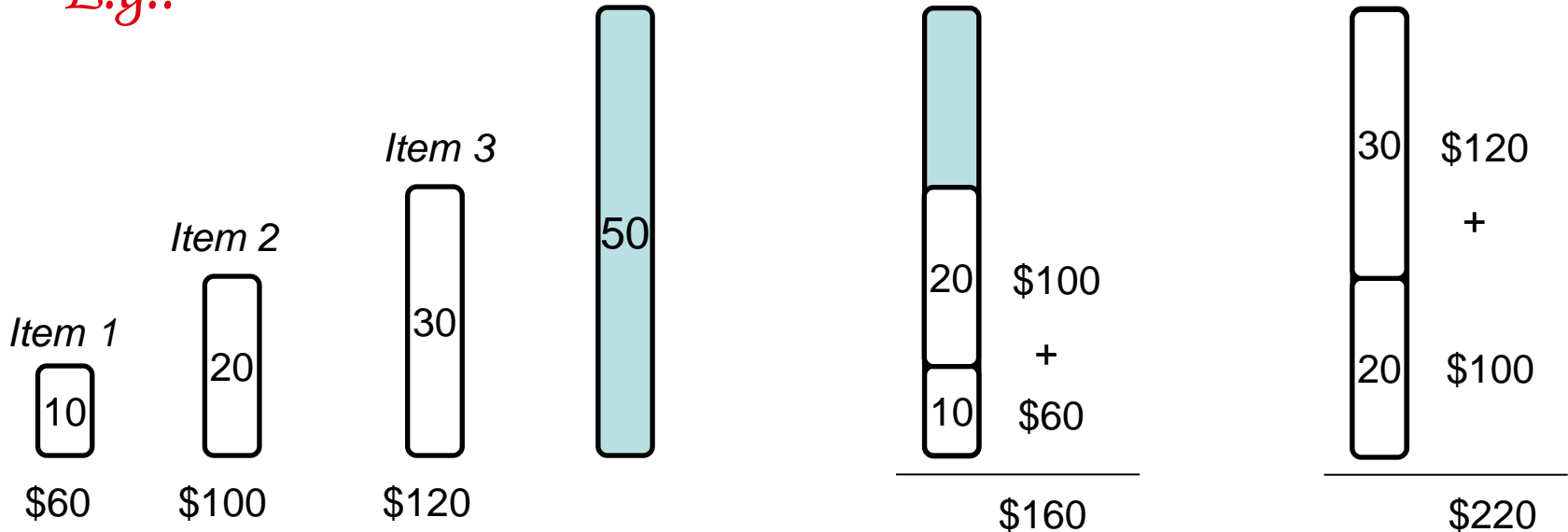
- Similar to above
- The thief can take fractions of items

The 0-1 Knapsack Problem

- Thief has a knapsack of capacity W
- There are n items: for i -th item value v_i and weight w_i
- Goal:
 - find x_i such that for all $x_i = \{0, 1\}$, $i = 1, 2, \dots, n$
 $\sum w_i x_i \leq W$ and
 $\sum x_i v_i$ is maximum

0-1 Knapsack - Greedy Strategy

• *E.g.:*



\$6/pound \$5/pound \$4/pound

- None of the solutions involving the greedy choice (item 1) leads to an optimal solution
 - The greedy choice property does not hold

0-1 Knapsack - Dynamic Programming

- $P(i, w)$ – the maximum profit that can be obtained from items 1 to i , if the knapsack has size w

- Case 1: thief takes item i

$$P(i, w) = v_i + P(i - 1, w - w_i)$$

- Case 2: thief does not take item i

$$P(i, w) = P(i - 1, w)$$

0-1 Knapsack - Dynamic Programming

$$P(i, w) = \max \left\{ \overbrace{v_i + P(i-1, w-w_i)}^{\text{Item } i \text{ was taken}}, \overbrace{P(i-1, w)}^{\text{Item } i \text{ was not taken}} \right\}$$

The diagram illustrates a 2D grid with rows indexed from 0 to n and columns indexed from 0 to W . The first two rows are labeled "first" and "second". The grid contains blue arrows representing operations. A specific cell at row i , column w is highlighted in light blue. A dashed blue line is at column $w - w_i$. An arrow points from the highlighted cell to the dashed line.

Example:

W = 5

$$P(i, w) = \max \{v_i + P(i - 1, w-w_i), P(i - 1, w)\}$$

Item	Weight	Value
1	2	12
2	1	10
3	3	20
4	2	15

	0	1	2	3	4	5
0	0	0	0	0	0	0
1	0	0	12	12	12	12
2	0	10	12	22	22	22
3	0	10	12	22	30	32
4	0	10	15	25	30	37

$$P(1, 1) = P(0, 1) = 0$$

$$P(1, 2) = \max\{12+0, 0\} = 12$$

$$P(1, 3) = \max\{12+0, 0\} = 12$$

$$P(1, 4) = \max\{12+0, 0\} = 12$$

$$P(1, 5) = \max\{12+0, 0\} = 12$$

$$P(2, 1) = \max\{10+0, 0\} = 10$$

$$P(2, 2) = \max\{10+0, 12\} = 12$$

$$P(2, 3) = \max\{10+12, 12\} = 22$$

$$P(2, 4) = \max\{10+12, 12\} = 22$$

$$P(2, 5) = \max\{10+12, 12\} = 22$$

$$P(3, 1) = P(2, 1) = 10$$

$$P(3, 2) = P(2, 2) = 12$$

$$P(3, 3) = \max\{20+0, 22\} = 22$$

$$P(3, 4) = \max\{20+10, 22\} = 30$$

$$P(3, 5) = \max\{20+12, 22\} = 32$$

$$P(4, 1) = P(3, 1) = 10$$

$$P(4, 2) = \max\{15+0, 12\} = 15$$

$$P(4, 3) = \max\{15+10, 22\} = 25$$

$$P(4, 4) = \max\{15+12, 30\} = 30$$

$$P(4, 5) = \max\{15+22, 32\} = 37$$

Reconstructing the Optimal Solution

	0	1	2	3	4	5
0	0	0	0	0	0	0
1	0	0	12	12	12	12
2	0	10	12	22	22	22
3	0	10	12	22	30	32
4	0	10	15	25	30	37

- Item 4
- Item 2
- Item 1

- Start at $P(n, W)$
- When you go left-up \Rightarrow item i has been taken
- When you go straight up \Rightarrow item i has not been taken

Overlapping Subproblems

$$P(i, w) = \max \{v_i + P(i - 1, w - w_i), P(i - 1, w)\}$$

	0	1				w					W
0	0	0	0	0	0	0	0	0	0	0	0
	0										
	0										
i-1	0										
i	0										
	0										
n	0										

E.g.: all the subproblems shown in grey may depend on $P(i-1, w)$

Sudocode

```
main()
{
    int P[5]={0,1,2,5,6};
    int wt[5]={0,2,3,4,5};
    int m=8, n=4;
    int k[5][9];

    for(int i=0; i<=n; i++)
    {
        for(int w=0; w<=m; w++)
        {
            if(i==0 || w==0)
                k[i][w]=0;
            else if(wt[i] <= w)
                k[i][w]=max(P[i]+k[i-1][w-wt[i]],
                             k[i-1][w]);
            else k[i][w]=k[i-1][w];
        }
    }
    cout << k[n][w];
}
```

Thanks All