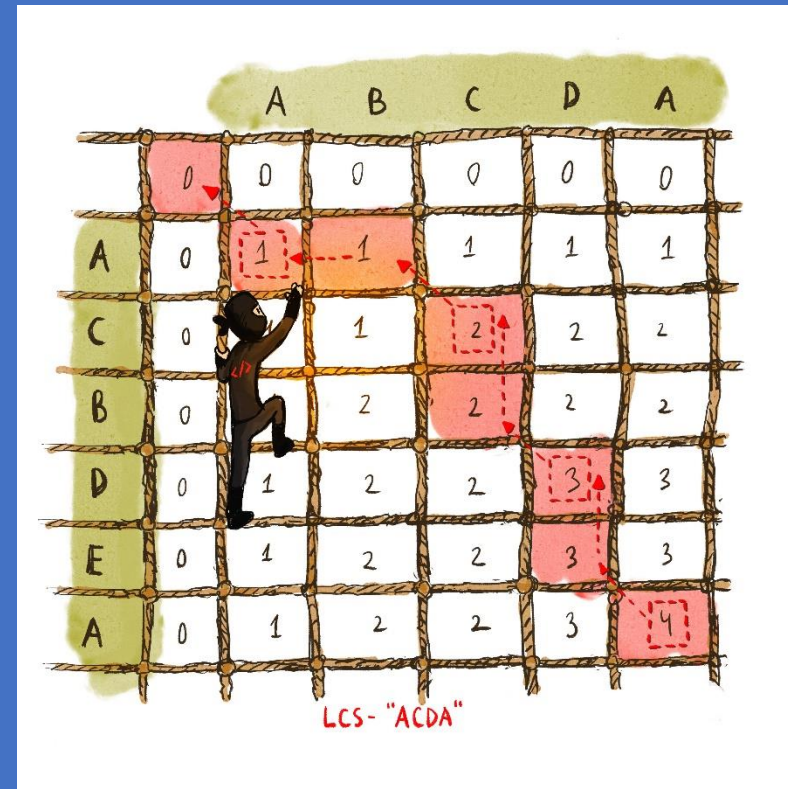


# Dynamic Programming

Yan Gu

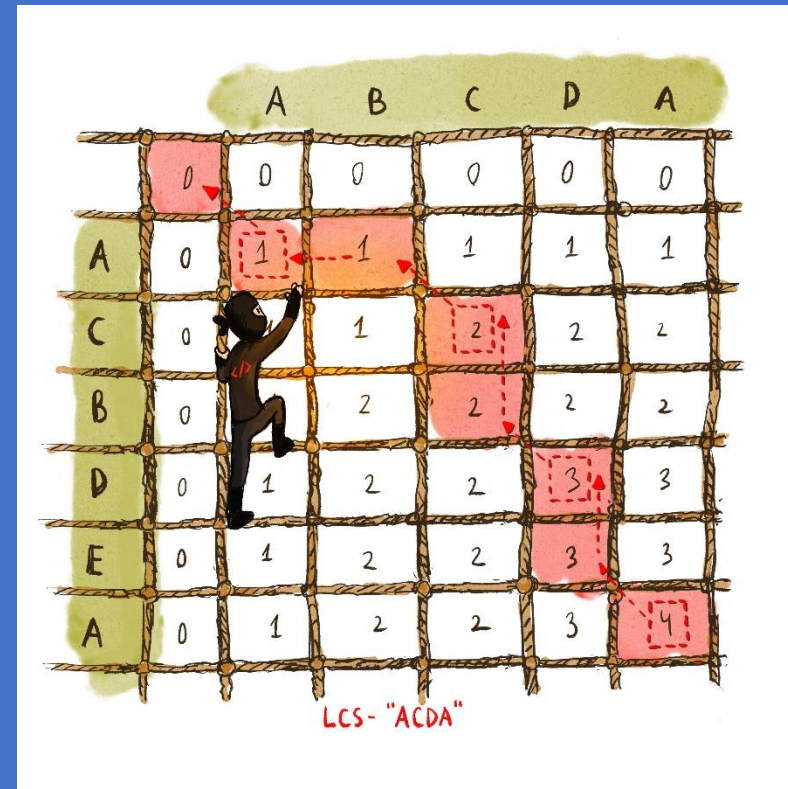


# Class announcement

- **We do not know your emergency situations (e.g., an active COVID case), so if you think you need to let us know, please inform us via an email, on campuswire, or on a private message on the slack channel**
- **Midterm: 6:30-8:30pm Oct 28, MSE 116**
- **Similarly, if you have a conflict, please inform us via email/campuswire/slack since we need to your information to discuss more details**
- **Basically if you need to start a bit earlier or later (like between 6-7pm), that's easy to handle (but you need to let us know)**
- **It will be harder if you want to do it in a non-overlapping time: we will review it in a case-by-case manner**
  - **It's definitely resolvable, but I don't recommend that personally**

# Dynamic Programming

Yan Gu



# What cannot be solved by greedy strategies?

- Different candies have different “values” (say, how much you like them)
- With a fixed budget of  $S$  dollars, how to maximize the total value?
- No known greedy algorithm can solve this ☹
- A lot of variants: 0/1 knapsack, unlimited knapsack, k-knapsack, ...

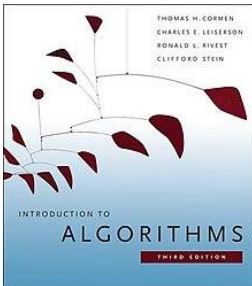
	<p>Value = 1 \$2</p> 	<p>Value = 2 \$4</p> 	<p>Value = 4 \$7</p> 	<p>Value = 20 \$15</p> 
<p>\$5 Value = 2</p>	<p>\$5 Value = 3</p> 			
	<p>\$1 Value = 1</p> 		<p>\$7 Value = 5</p> 	<p>\$9 Value = 3</p> 

# Knapsack problem

- Your little brother is attending university this year
- Unfortunately, he did not get an offer from UCR, and he has to go to the east coast, and needs to take a flight



\$50, 1lb



\$70, 5lb



\$1500, 8lb



\$80, 2lb



# A simplified case: unlimited knapsack

- Overall weight limit: 8 lb, we can take an unlimited number of each item
  - Item 1: 5 lb, \$150
  - Item 2: 4 lb, \$100
  - Item 3: 2 lb, \$10
- 
- Expensive first: Item 1 + Item 3, value: \$160
  - Lightest first: Item 3 \* 4, value \$40
  - Optimal: Item 2 \* 2, value: \$200
- 
- Greedy strategy does not provide the optimal solution
  - A naïve solution? Try all possibilities!

# A naïve algorithm

Item 1: 5 lb, \$150  
Item 2: 4 lb, \$100  
Item 3: 2 lb, \$10

suitcase(8):

Case 1: first put item 1,  
total value = suitcase(3) + 150

Case 2: first put item 2,  
total value = suitcase(4) + 100

Case 3: first put item 3,  
total value = suitcase(6) + 10

Best = max of the above three

```
int suitcase(int leftWeight) {  
    int curBest = 0;  
    foreach item of (weight, value)  
        if (leftWeight >= weight)  
            curBest = max(curBest, suitcase(leftWeight - weight) + value);  
    return curBest;  
}
```



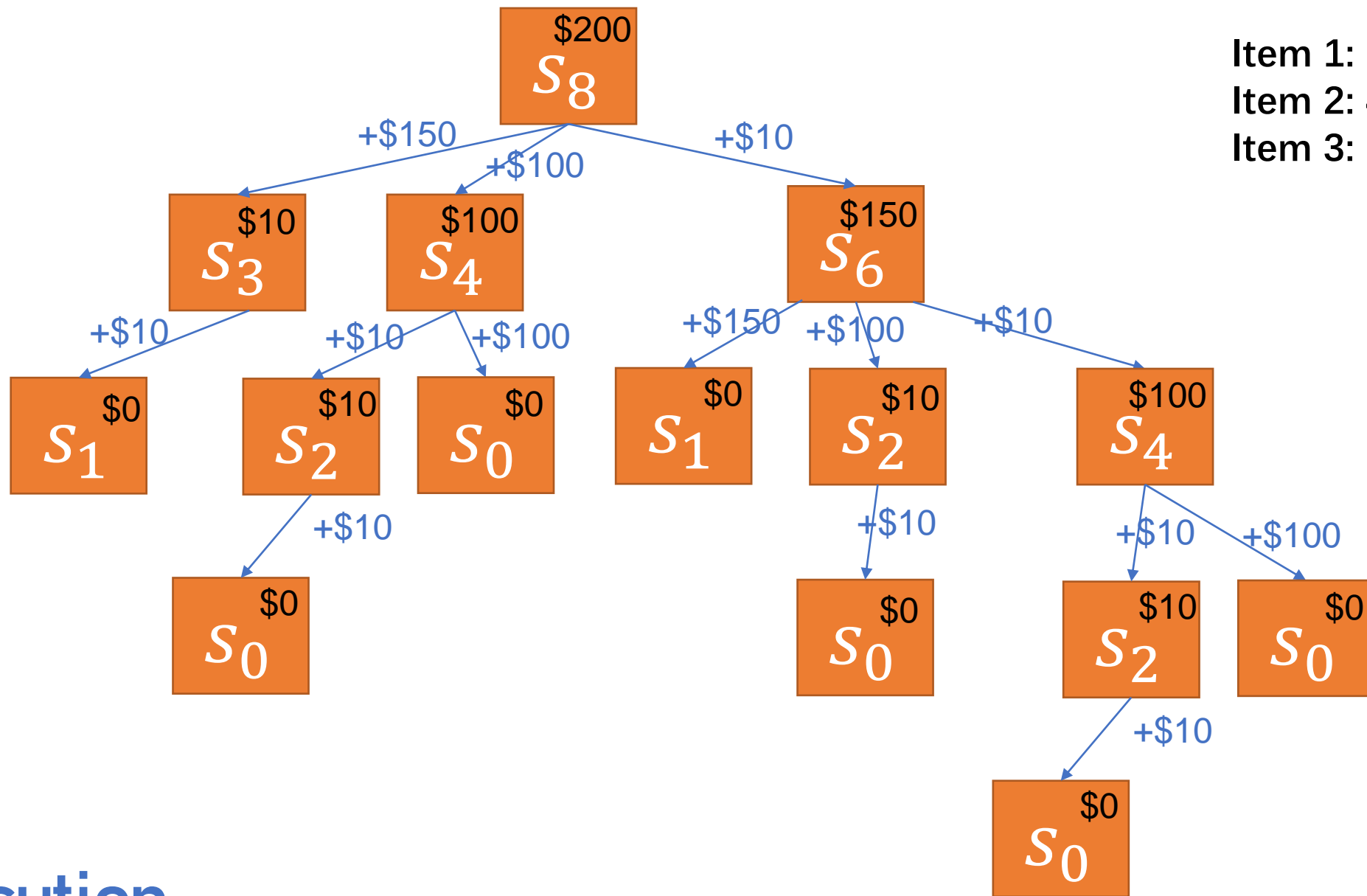
Recursive call

```
answer = suitcase(8);
```

This algorithm takes exponential time, and only works for very small instances



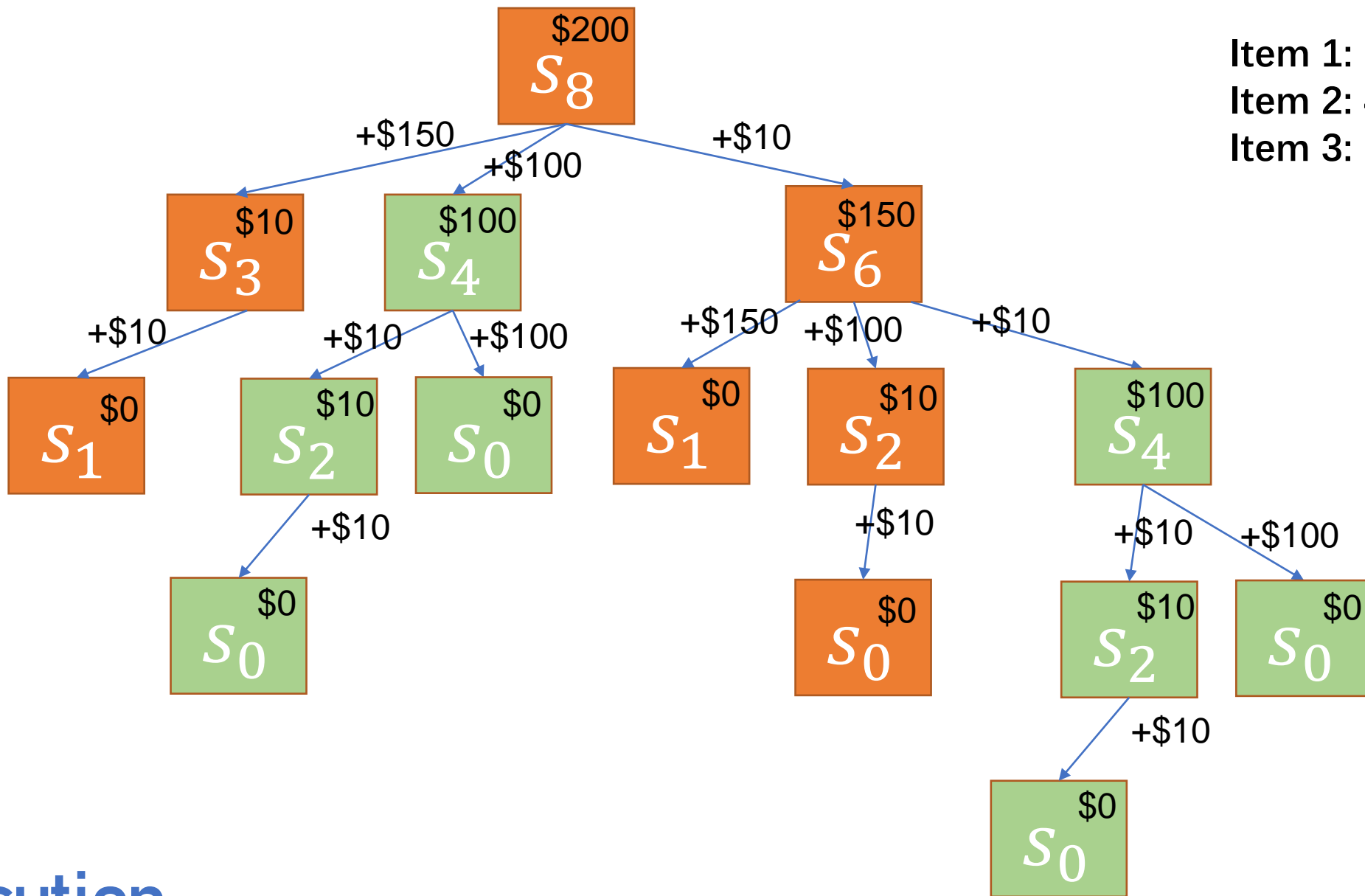
Item 1: 5 lb, \$150  
Item 2: 4 lb, \$100  
Item 3: 2 lb, \$10



Execution  
Recurrence Tree

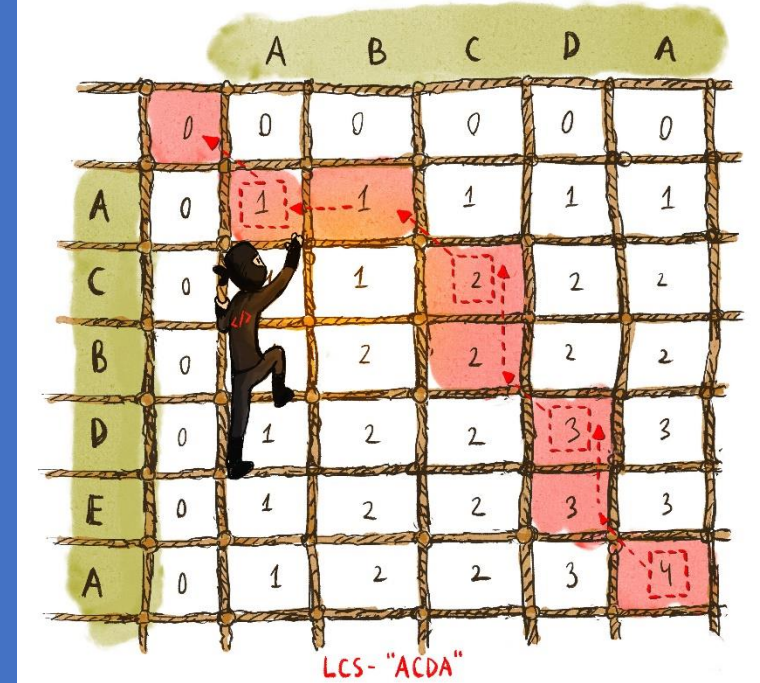


Item 1: 5 lb, \$150  
 Item 2: 4 lb, \$100  
 Item 3: 2 lb, \$10



Execution  
 Recurrence Tree

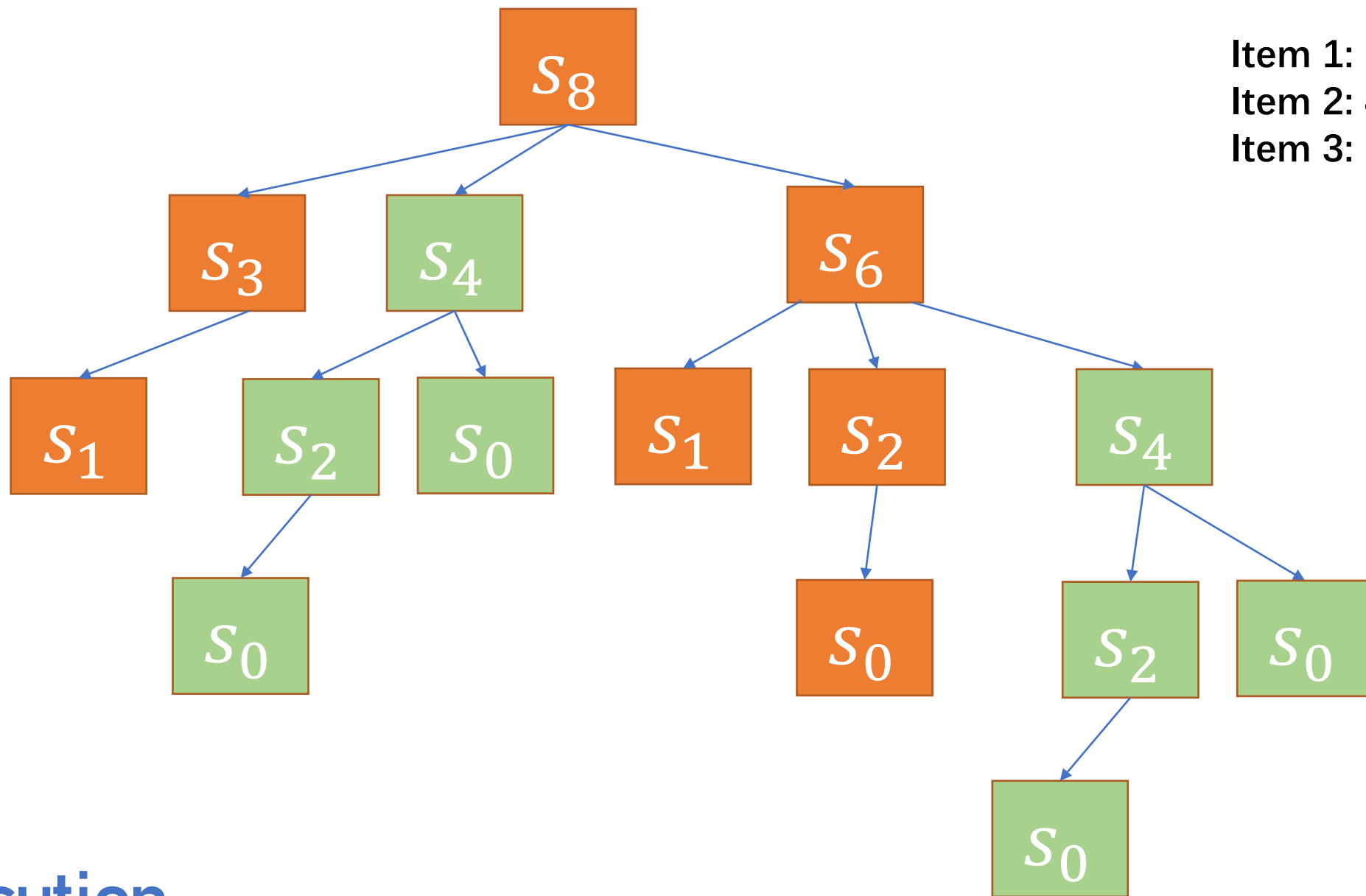
Next 3.5 lectures:  
Dynamic  
Programming



# Programming?

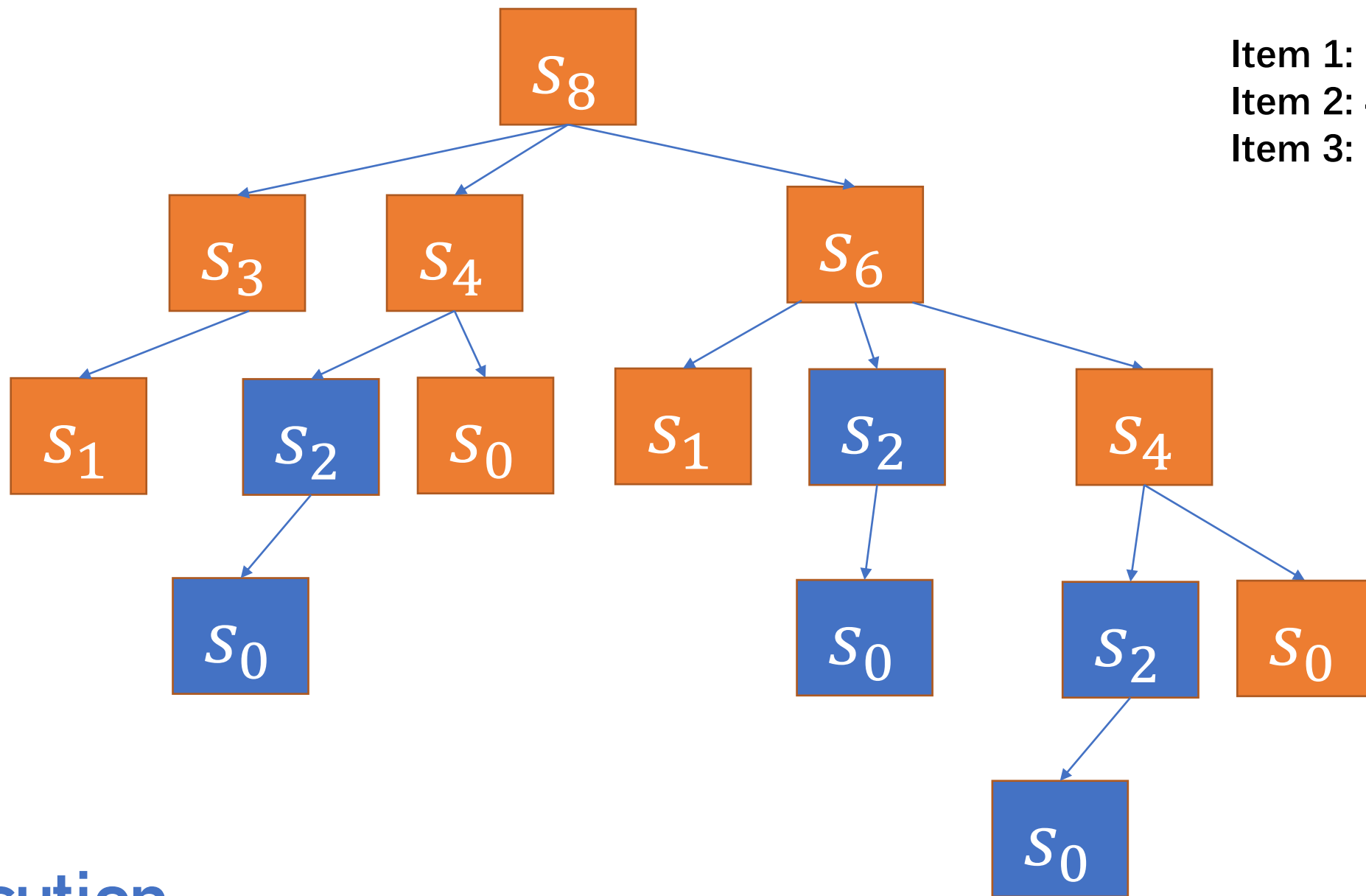
- **Program (noun)** \ 'prō-, gram , -grəm \
  - a sequence of coded instructions that can be inserted into a mechanism (such as a computer)
- **Programming (noun)** \ 'prō-, gra-minj , -grə-\
  - a plan of action to accomplish a specified end
- **In dynamic programming, or linear programming, the word programming means a “tabular solution method”**
  - In fact, the concept of dynamic programming was proposed before computers, and was a subarea of operating research
  - Without a computer and memory, you have to write down the intermediate results on a piece of paper, and in a table

Item 1: 5 lb, \$150  
Item 2: 4 lb, \$100  
Item 3: 2 lb, \$10



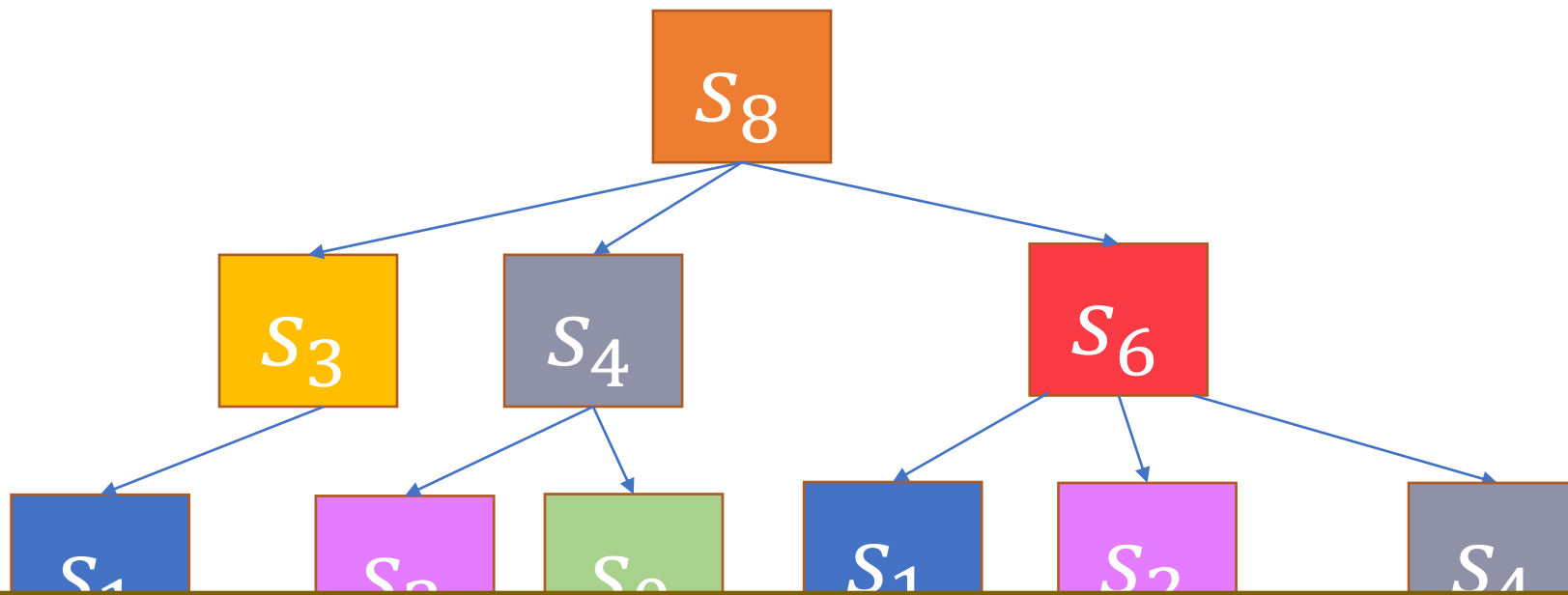
Execution  
Recurrence Tree

Item 1: 5 lb, \$150  
Item 2: 4 lb, \$100  
Item 3: 2 lb, \$10

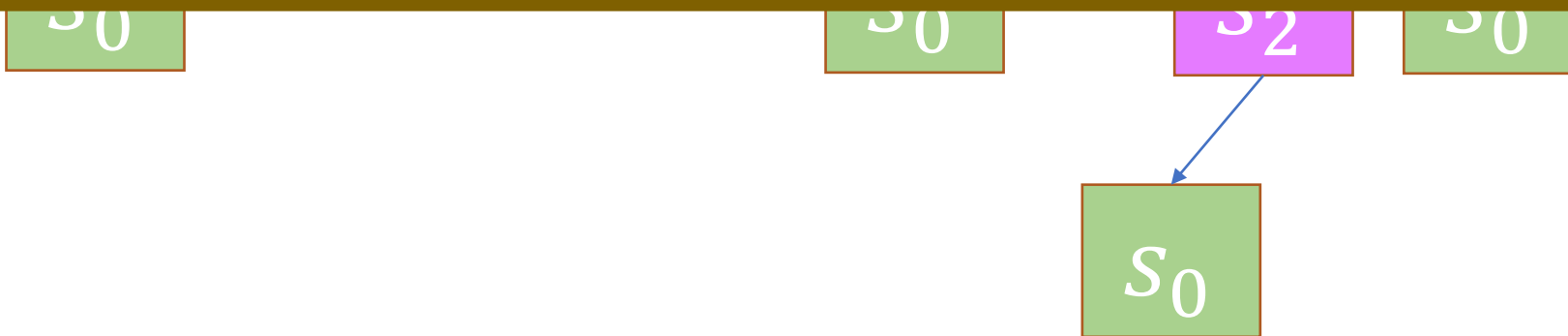


Execution  
Recurrence Tree

Item 1: 5 lb, \$150  
Item 2: 4 lb, \$100  
Item 3: 2 lb, \$10



There are indeed at most 9 different values that can be computed from this enormous recurrence tree



Execution  
Recurrence Tree

# A naïve algorithm

```
int suitcase(int leftWeight) {  
    int curBest = 0;  
    foreach item (weight, value)  
        if (leftWeight >= weight)  
            curBest = max(curBest, suitcase(leftWeight - weight) + value);  
    return curBest;  
}
```

```
answer = suitcase(8);
```



# A DP algorithm

```
int suitcase(int leftWeight) {  
    if (ans[leftWeight] != -1) return ans[leftWeight];  
    int curBest = 0;  
    foreach item (weight, value)  
        if (leftWeight >= weight)  
            curBest = max(curBest, suitcase(leftWeight - weight) + value);  
    return ans[leftWeight] = curBest;  
}
```

```
int ans[0..8] = {-1, ... , -1};  
answer = suitcase(8);
```

# A naïve algorithm

```
int suitcase(int leftWeight) {  
    int curBest = 0;  
    foreach item of (weight, value)  
        if (leftWeight >= weight)  
            curBest = max(curBest, suitcase(leftWeight - weight) + value);  
    return curBest;  
}
```

answer = suitcase(8);

$$s_i = \max \begin{cases} 0 \\ \max_{(w_j, v_j) \text{ is an item}} \{s_{i-w_j} + v_j\} \mid i \geq w_j \end{cases}$$

# Recursive Solution

- Define  $s_i$  as the maximum value you can get for a total weight of  $i$
- We can express  $s_i$  as the following **recurrence**:

$$s_i = \max \left\{ \begin{array}{l} 0 \\ \max_{(w_j, v_j) \text{ is an item}} \{s_{i-w_j} + v_j\} \mid i \geq w_j \end{array} \right.$$

- Final answer is  $s_k$  ( $k$  is the weight limit)

# Optimal Substructure

- The problem is to find the optimal value  $s_i$  for a total weight of  $i$
- What is the best solution with item  $j$ ?

Item 1: 5 lb, \$150  
Item 2: 4 lb, \$100  
Item 3: 2 lb, \$10

suitcase(8):

Case 1: first put item 1,  
total value = suitcase(3) + 150

Case 2: first put item 2,  
total value = suitcase(4) + 100

Case 3: first put item 3,  
total value = suitcase(6) + 10

Best = max of the above three

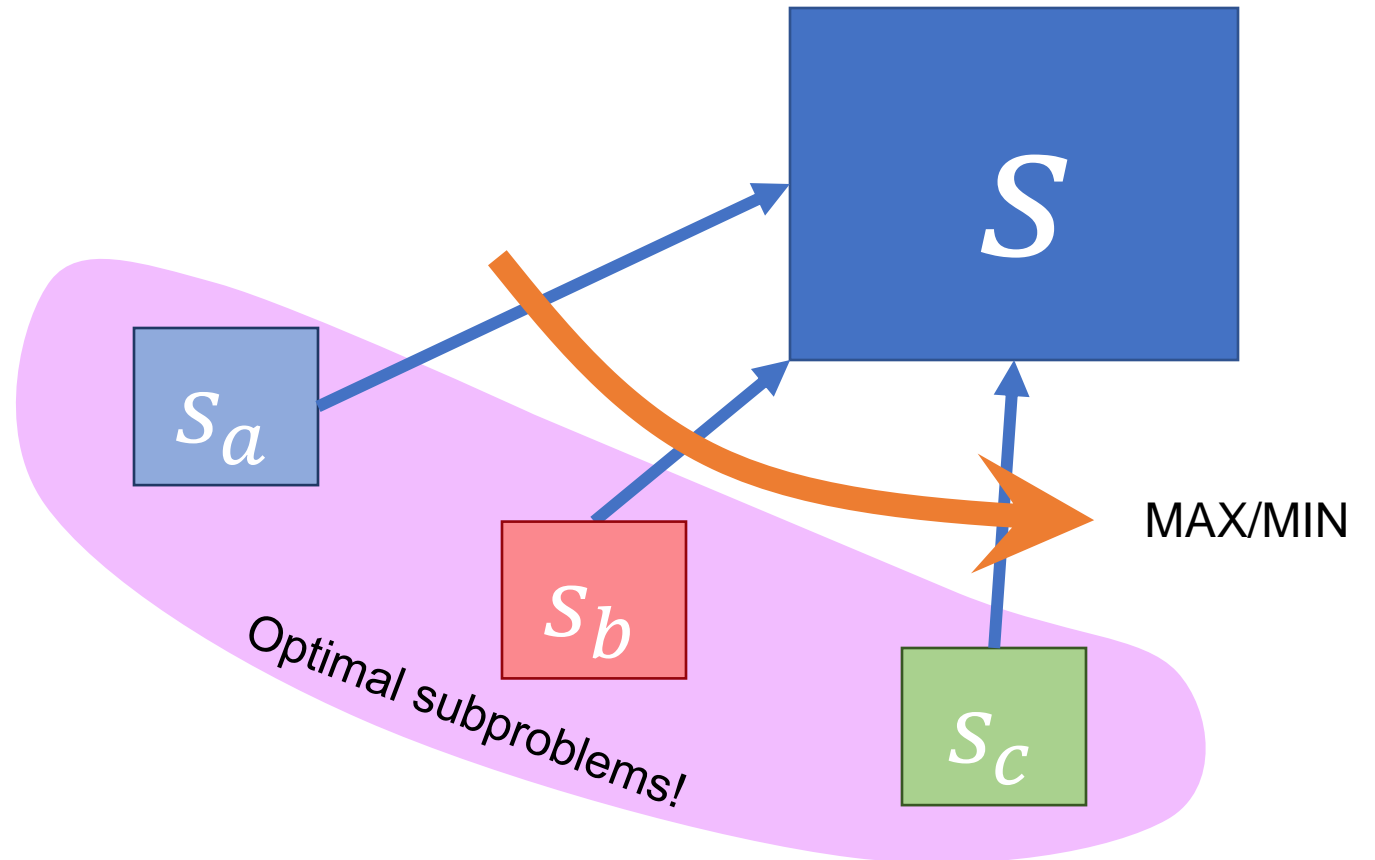
- The rest must be the optimal solution when we have weight limit  $i - w_j$ !
- The same problem with new weight limit  $i - w_j$ !
- That's  $s_{i-w_j}$ ! (optimal substructure again!)

# What is dynamic programming?

$$s_i = \max \begin{cases} 0 \\ \max_{(w_j, v_j) \text{ is an item}} \{s_{i-w_j} + v_j\} \mid i > w_j \end{cases}$$

The goal is to **avoid** computing any  $s_i$  multiple times!

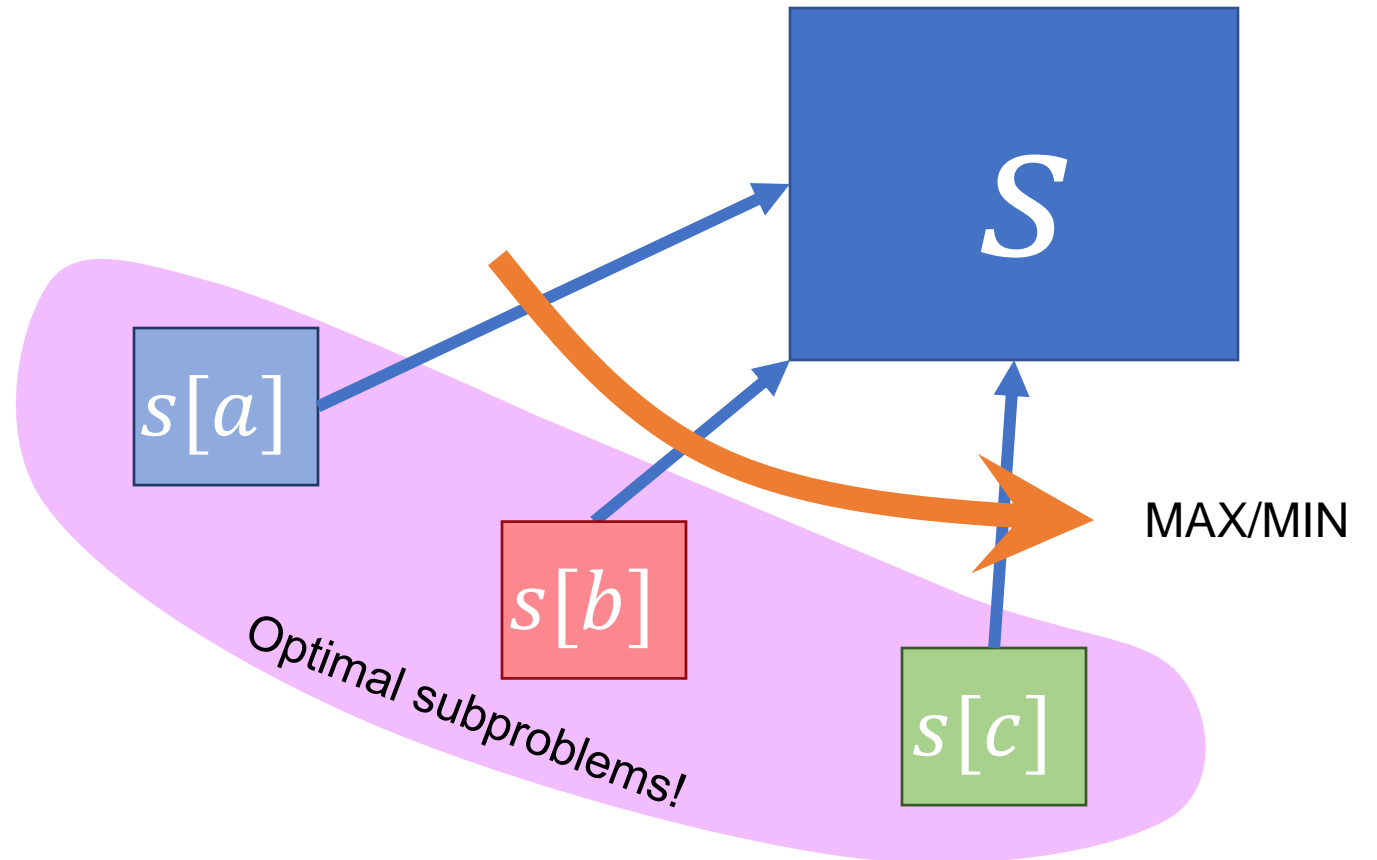
How can we “**memorize**” the values of  $s_{i-w_j}$ ?



# What is dynamic programming?

$$s[i] = \max \begin{cases} 0 \\ \max_{(w_j, v_j) \text{ is an item}} \{s[i - w_j] + v_j\} \mid i > w_j \end{cases}$$

Use an array!



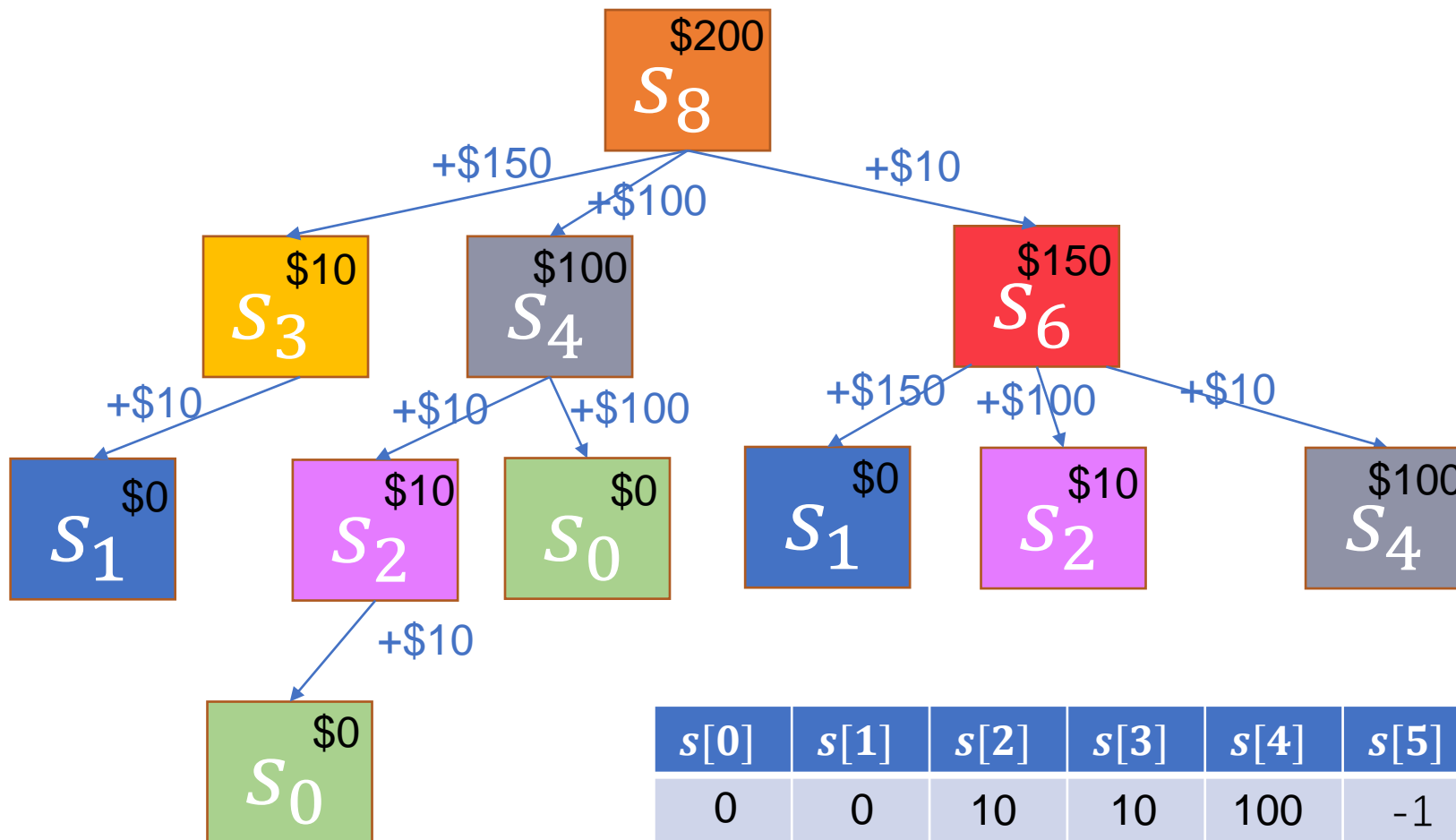
# A DP algorithm

```
int suitcase(int leftWeight) {  
    if (ans[leftWeight] != -1) return ans[leftWeight];  
    int curBest = 0;  
    foreach item (weight, value)  
        if (leftWeight >= weight)  
            curBest = max(curBest, suitcase(leftWeight - Weight) + value);  
    return ans[leftWeight] = curBest;  
}
```

```
int ans[0..8] = {-1, ... , -1};  
answer = suitcase(8);
```



Item 1: 5 lb, \$150  
 Item 2: 4 lb, \$100  
 Item 3: 2 lb, \$10

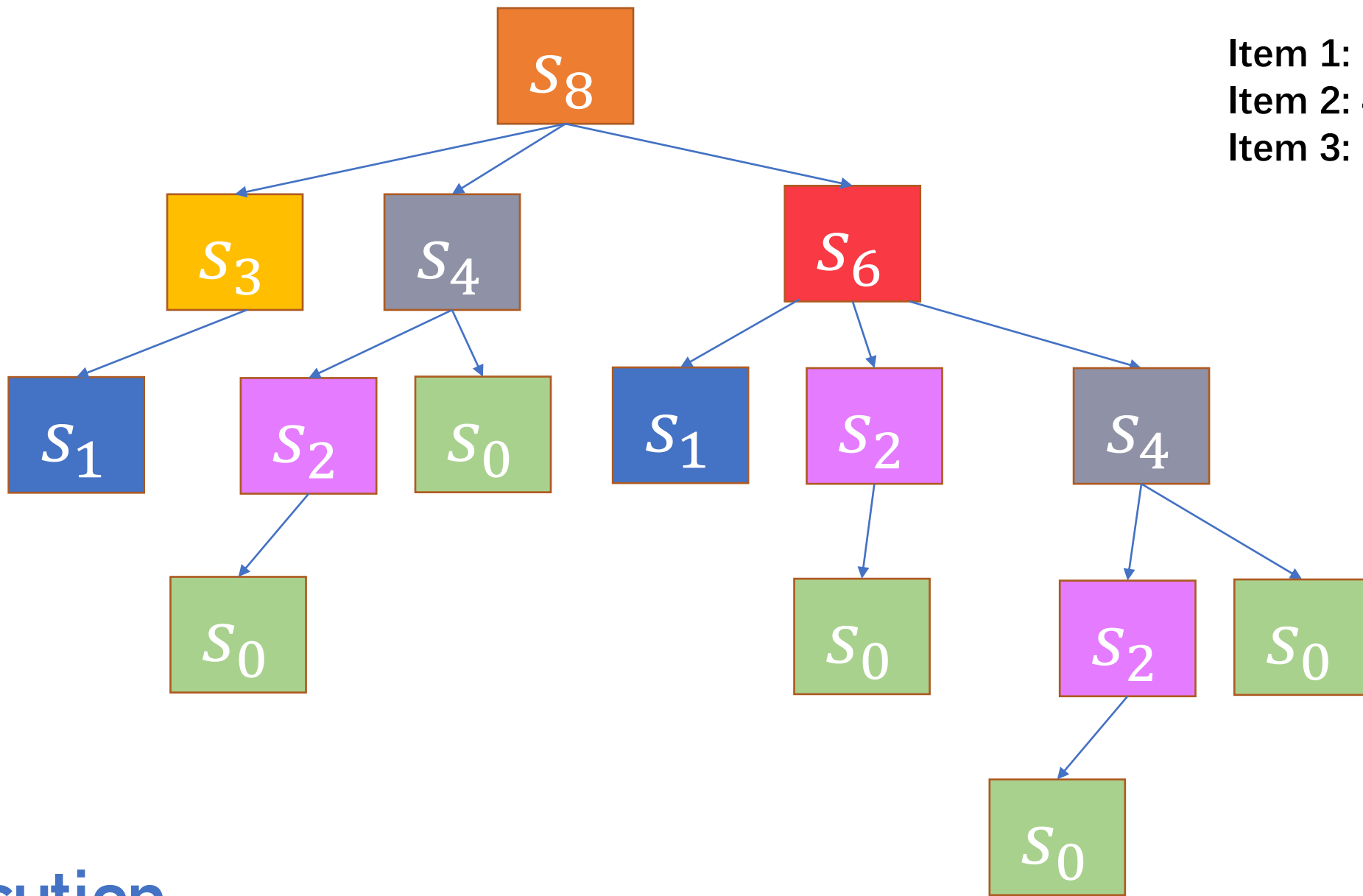


$s[0]$	$s[1]$	$s[2]$	$s[3]$	$s[4]$	$s[5]$	$s[6]$	$s[7]$	$s[8]$
0	0	10	10	100	-1	150	-1	200

$\Theta(nk)$  cost  
 where  $n$  is #items  
 $k$  is weight limit

Execution  
 Recurrence Tree

Item 1: 5 lb, \$150  
Item 2: 4 lb, \$100  
Item 3: 2 lb, \$10



Execution  
Recurrence Tree

# What is dynamic programming?

- Optimal substructure (**states**)

- What defines a subproblem?
  - weight limit
- What should be memorized as the index/value of your array?
  - The best value of a given weight limit

$$s[i] = \max \begin{cases} 0 \\ \max_{(w_j, v_j) \text{ is an item}} \{s[i - w_j] + v_j\} \mid i > w_j \end{cases}$$

- The **decisions**

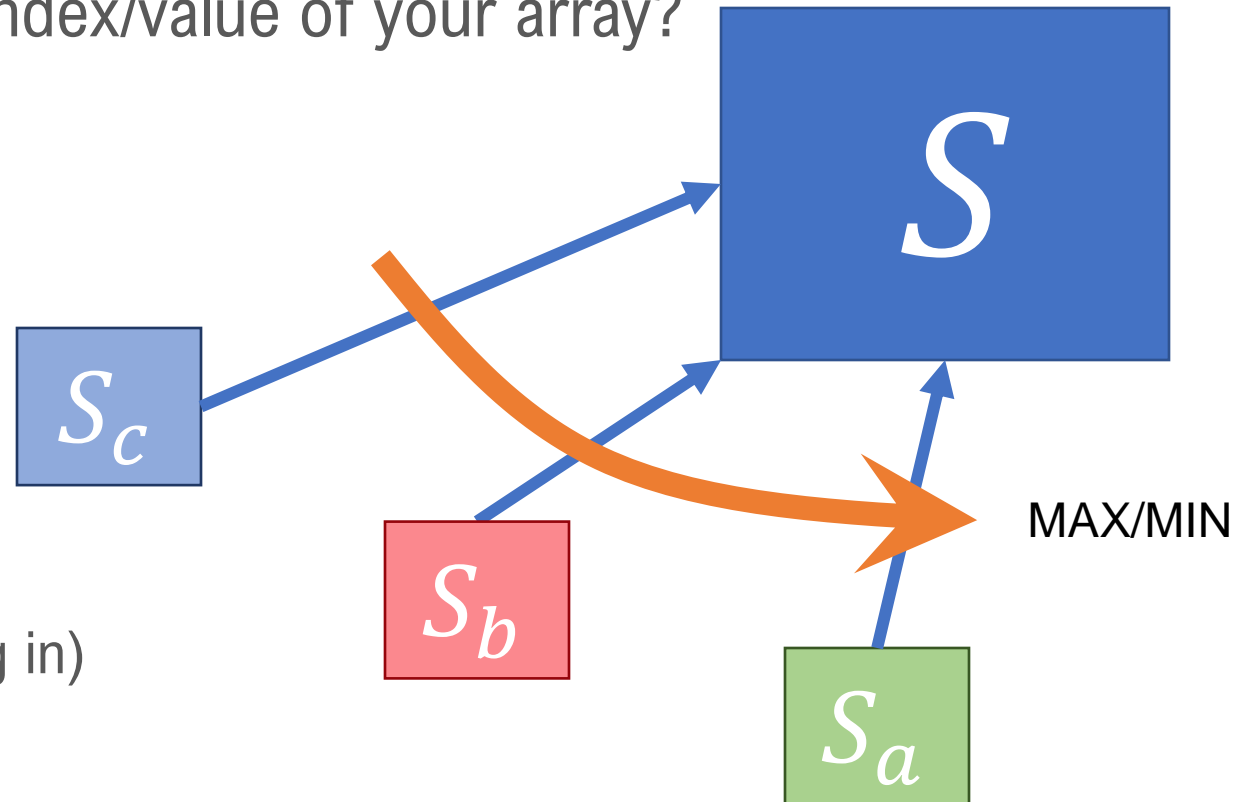
- What are the possible “last move”?
  - Put in item 1, 2, 3, ...
- Take a min or max?

- **Boundary**

- What are the base cases?
  - $s[i]$  is at least 0 (when we put nothing in)

- **Recurrence**

- Compute current state from previous states



# Is the previous solution perfect?

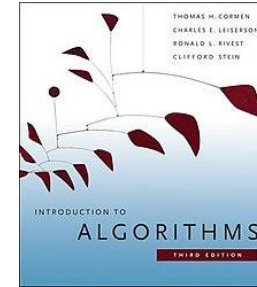
```
int suitcase(int leftWeight) {  
    if (ans[leftWeight] != -1) return ans[leftWeight];  
    int curBest = 0;  
    foreach item of (weight, value)  
        if (leftWeight >= weight)  
            curBest = max(curBest, suitcase(leftWeight -  
                Weight) + value);  
    return ans[leftWeight] = curBest;  
}  
int ans[8] = {-1, ... , -1};  
answer = suitcase(8);
```



\$50, 1lb



\$1500, 12lb



\$70, 5lb



\$80, 2lb



# Is this solution still correct if we only allow to use an item once?

```
int suitcase(int leftWeight) {  
    if (ans[leftWeight] != -1) return ans[leftWeight];  
    int curBest = 0;  
    foreach item of (weight, value)  
        if (leftWeight >= weight)  
            curBest = max(curBest, suitcase(leftWeight -  
                Weight) + value);  
    return ans[leftWeight] = curBest;  
}  
int ans[8] = {-1, ... , -1};  
answer = suitcase(8);
```



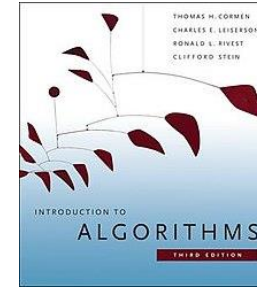
\$50, 1lb



\$50, 1lb



\$1500, 12lb



\$70, 5lb



\$80, 2lb



# Why the solution doesn't work for 0/1 knapsack?

- What is the “optimal subproblem”?
- After we choose item  $j$ , is the leftover problem “best value of weight limit  $k - w_j$ ”?
- No! It's “best value of weight limit  $k - w_j$  **and we cannot use item  $j$  again**”!
- How can we change the state to accommodate this?
- The subproblem we use must not contain item  $j$ !
- Add another dimension!

# What is the optimal substructure for the new problem?

- Let  $s[i, j]$  be the optimal value for total weight  $i$  using **only the first  $j$  items**

- How to calculate  $s[i, j]$ ? There are two options:

- Use the item  $j$  (value of  $j$  + best solution of weight limit  $i - w_j$  using first  $j-1$  items)

$$s[i - w_j, j - 1] + v_j$$

- Do not use item  $j$  (best solution of weight limit  $i$  using first  $j-1$  items)

$$s[i, j - 1]$$

- We added a dimension (“first  $i$  items”): the current “stage”
- The subproblem does not contain item  $j$ !



# Recurrence for 0/1 knapsack

- **The recurrence:**

$$s[i, j] = \max \begin{cases} s[i, j - 1] \\ s[i - w_j, j - 1] + v_j \end{cases} \quad i \geq w_j$$

- **The boundary:**  $s[i, 0] = 0$

# The DP implementation

```
int suitcase(int i, int j) {  
    if (ans[i][j] != -1) return ans[i][j];  
    if (j == 0) return 0;  
    int best = suitcase(i, j-1);  
    if (i >= weight[j]) best = max(best, suitcase(i-weight[j], j-1)+value[j]);  
    return ans[i][j] = best;  
}
```

```
int ans[n][k] = {-1, ... , -1};  
answer = suitcase(n, k);
```

# A non-recursive implementation

```
int ans[i][0] = {0, ... , 0};  
for j = 1 to k do  
    for i = 0 to n do {  
        ans[i][j] = ans[i][j-1];  
        if (i >= weight[j])  
            ans[i][j] = max(ans[i][j], ans[i-weight[j]][j-1]+value[j]);  
    }  
return ans[n][k];
```

- Generally, be careful to use the non-recursive implementation — easy to err if a state that should be computed is actually not

# An even simpler implementation

```
int ans[i] = {0, ... , 0};  
for j = 1 to k do  
    for i = n downto weight[j] do  
        ans[i] = max(ans[i], ans[i-weight[j]] + value[j]);  
return ans[n];
```

- We only need to store a 1D array

# The simpler implementation for the first problem

```
int ans[i] = {0, ... , 0};  
for j = 1 to k do  
    for i = weight[j] to n do  
        ans[i] = max(ans[i], ans[i-weight[j]] + value[j]);  
return ans[n];
```

- We only need to store a 1D array
- As the bonus question in the assignment, you show that these two implementations are correct

# The famous knapsack problem

- Put some items in a weight-limited container under some certain rules, and maximize the total value
- Believe it or not, suitcases (especially with telescopic handle and wheels) are pretty new: history of suitcases
- The first problem is referred to as the unbounded knapsack problem (UKP)
- The second problem is referred to as the 0-1 knapsack problem
- Multiple knapsack problem: item  $j$  has  $x_j$  copies
- Combinations of the previous three
- Each item has more than one dimension (e.g., both weight and size)

# Conclusion for today's lecture

- **We introduce the concept of “dynamic programming” (DP)**
  - DP is not an algorithm, but an algorithm design idea (methodology)
  - DP works on problems with optimal substructure
- **A DP recurrence of the states (possibly with stages), decisions, with boundary cases**
- **We can convert a DP recurrence to a DP algorithm**
  - Recursive implementation: straightforward
  - Non-recursive implementation: faster, and easy to be optimized



# Conclusion for today's lecture

- **The best way to improve the understanding of DP is by practicing**
  - A few more examples in the next two lectures
  - We gave you 11 problems in the assignments (5 mandatory and 6 bonus), please try as many as possible
  - I do not use the examples in CLRS, and you can read Chapter 15 in CLRS with new examples, and work on the additional questions in the book