

# CS473 - Algorithms I



## Other Dynamic Programming Problems

*View in slide-show mode*

# CS473 - Algorithms I



## Problem 1 Subset Sum

# Subset-Sum Problem

Given:

- a set of integers  $X = \{x_1, x_2, \dots, x_n\}$ , and
- an integer  $B$

Find:

- a subset of  $X$  that has **maximum sum not exceeding  $B$** .

Notation:  $S_{n,B} = \{x_1, x_2, \dots, x_n : B\}$  is the subset-sum problem

- *The integers to choose from:  $x_1, x_2, \dots, x_n$*
- *Desired sum:  $B$*

# Subset-Sum Problem

## Example:

$$S_{12,99}: \{ \overset{x_1}{20}, \overset{x_2}{30}, \overset{x_3}{14}, \overset{x_4}{70}, \overset{x_5}{40}, \overset{x_6}{50}, \overset{x_7}{15}, \overset{x_8}{25}, \overset{x_9}{80}, \overset{x_{10}}{60}, \overset{x_{11}}{10}, \overset{x_{12}}{95} : 99 \}$$

Find a subset of  $X$  with maximum sum not exceeding 99.

An optimal solution:

$$N_{\text{opt}} = \{ \overset{x_1}{20}, \overset{x_3}{14}, \overset{x_5}{40}, \overset{x_8}{25} \}$$

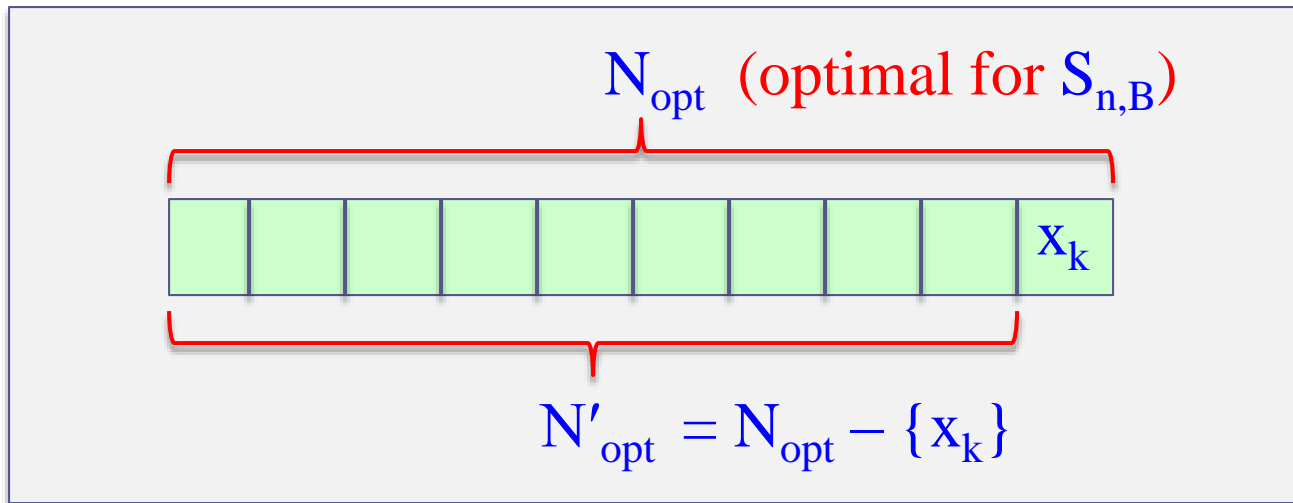
$$\text{with sum } 20 + 14 + 40 + 25 = 99$$

# Optimal Substructure Property

- Consider the solution as a sequence of  $n$  decisions:  
 *$i^{\text{th}}$  decision*: whether we pick number  $x_i$  or not

Let  $N_{\text{opt}}$  be an optimal solution for  $S_{n,B}$

Let  $x_k$  be the highest-indexed number in  $N_{\text{opt}}$

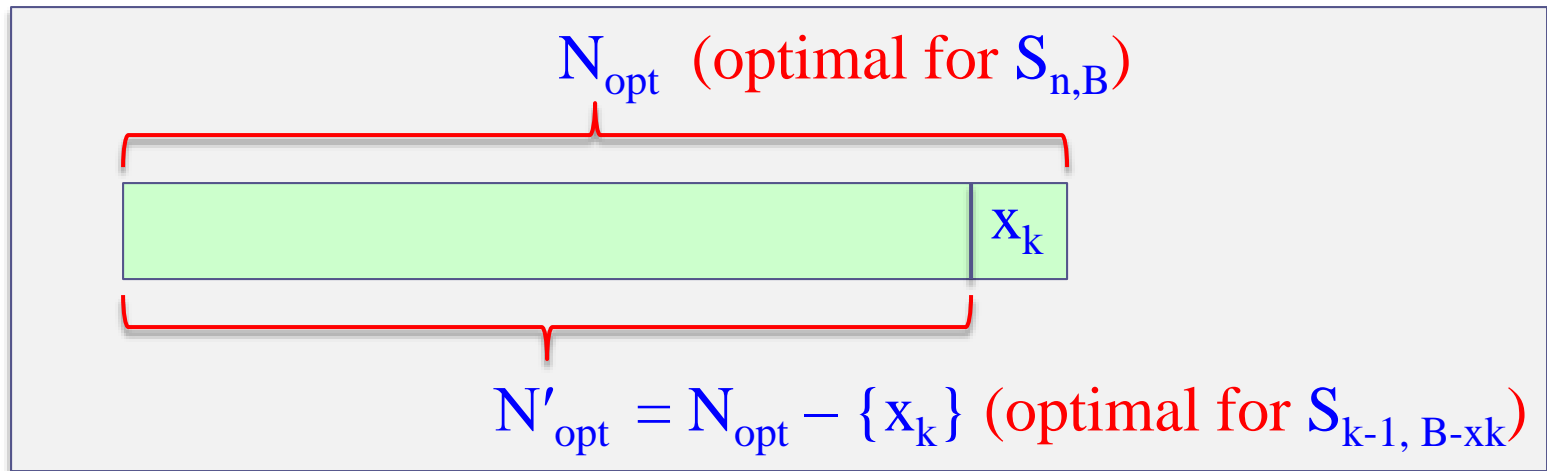


# Optimal Substructure Property

Lemma:  $N'_{\text{opt}} = N_{\text{opt}} - \{x_k\}$  is an optimal solution for  
the subproblem  $S_{k-1, B-x_k} = \{x_1, x_2, \dots, x_{k-1} : B-x_k\}$   
and

$$c(N_{\text{opt}}) = x_k + c(N'_{\text{opt}})$$

where  $c(N)$  is the sum of all numbers in subset  $N$



# Optimal Substructure Property - Proof

*Proof:* By contradiction, assume that there exists another solution  $A'$  for  $S_{k-1, B-x_k}$  for which:

$$c(A') > c(N'_{opt}) \text{ and } c(A') \leq B - x_k$$

*i.e.  $A'$  is a better solution than  $N'_{opt}$  for  $S_{k-1, B-x_k}$*

Then, we can construct  $A = A' \cup \{x_k\}$  as a solution to  $S_{k, B}$ .

We have:

$$\begin{aligned} c(A) &= c(A') + x_k \\ &> c(N'_{opt}) + x_k = c(N_{opt}) \end{aligned}$$

Contradiction!  $N_{opt}$  was assumed to be optimal for  $S_{k, B}$ .

Proof complete.

# Optimal Substructure Property - Example

Example:

$$S_{12,99}: \{ \overset{x_1}{20}, \overset{x_2}{30}, \overset{x_3}{14}, \overset{x_4}{70}, \overset{x_5}{40}, \overset{x_6}{50}, \overset{x_7}{15}, \overset{x_8}{25}, \overset{x_9}{80}, \overset{x_{10}}{60}, \overset{x_{11}}{10}, \overset{x_{12}}{95} : 99 \}$$

$$N_{\text{opt}} = \{ \overset{x_1}{20}, \overset{x_3}{14}, \overset{x_5}{40}, \overset{x_8}{25} \} \text{ is optimal for } S_{12,99}$$

$$N'_{\text{opt}} = N_{\text{opt}} - \{x_8\} = \{20, 14, 40\} \text{ is optimal for}$$

$$\text{the subproblem } S_{7,74} = \{ \overset{x_1}{20}, \overset{x_2}{30}, \overset{x_3}{14}, \overset{x_4}{70}, \overset{x_5}{40}, \overset{x_6}{50}, \overset{x_7}{15} : 74 \}$$

and

$$c(N_{\text{opt}}) = 25 + c(N'_{\text{opt}}) = 25 + 74 = 99$$



# Recursive Definition an Optimal Solution

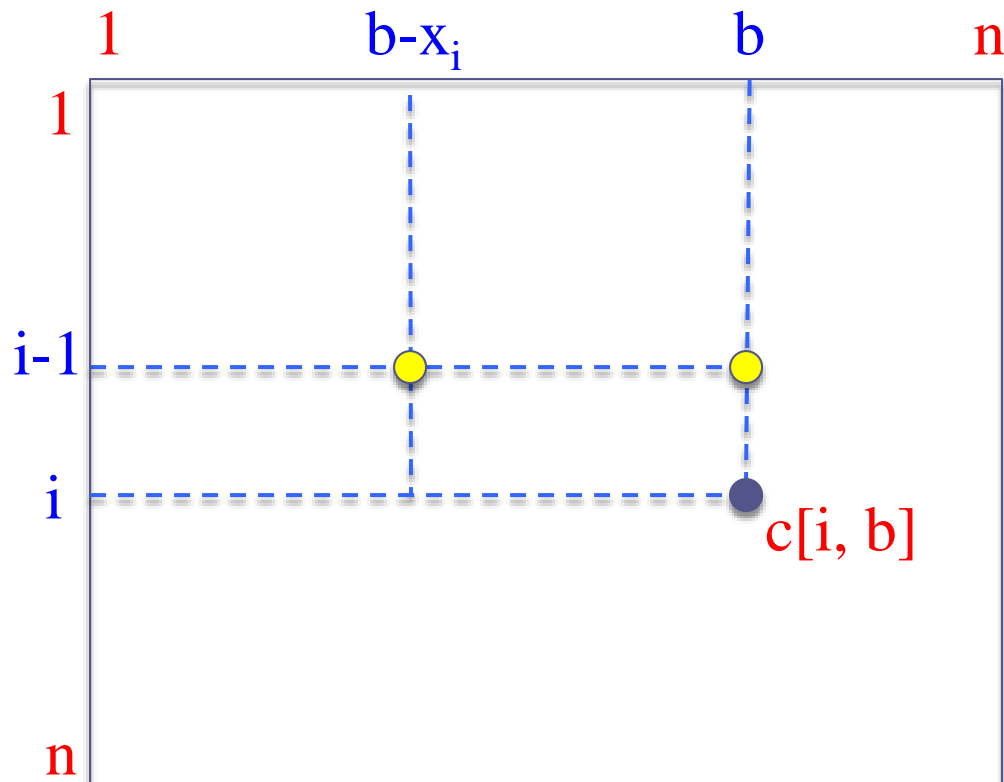
$c[i, b]$ : the value of an optimal solution for  $S_{i,b} = \{x_1, \dots, x_i: b\}$

$$c[i, b] = \begin{cases} 0 & \text{if } i = 0 \text{ or } b = 0 \\ c[i - 1, b] & \text{if } x_i > b \\ \text{Max}\{x_i + c[i - 1, b - x_i], c[i - 1, b]\} & \text{if } i > 0 \text{ and } b \geq x_i \end{cases}$$

According to this recurrence, an optimal solution  $N_{i,b}$  for  $S_{i,b}$ :

- either contains  $x_i \implies c(N_{i,b}) = x_i + c(N_{i-1, b-x_i})$
- or does not contain  $x_i \implies c(N_{i,b}) = c(N_{i-1, b})$

$$c[i, b] = \begin{cases} 0 & \text{if } i = 0 \text{ or } b = 0 \\ c[i - 1, b] & \text{if } x_i > b \\ \text{Max}\{x_i + c[i - 1, b - x_i], c[i - 1, b]\} & \text{if } i > 0 \text{ and } b \geq x_i \end{cases}$$



Need to process:

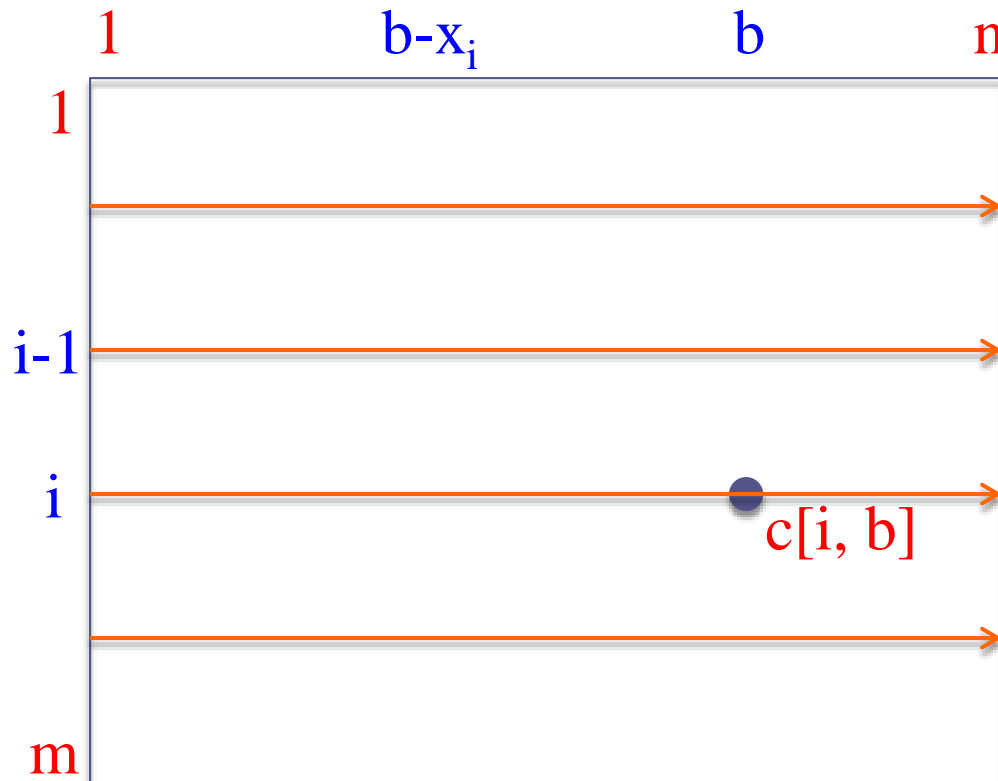
$c[i, b]$

after computing:

$c[i-1, b],$

$c[i-1, b-x_i]$

$$c[i, b] = \begin{cases} 0 & \text{if } i = 0 \text{ or } b = 0 \\ c[i - 1, b] & \text{if } x_i > b \\ \text{Max}\{x_i + c[i - 1, b - x_i], c[i - 1, b]\} & \text{if } i > 0 \text{ and } b \geq x_i \end{cases}$$



```

for i ← 1 to m
  for b ← 1 to n
    ...
    ...
    c[i, b] =
  
```

# Computing the Optimal Subset-Sum Value

## SUBSET-SUM ( $x, n, B$ )

**for**  $b \leftarrow 0$  **to**  $B$  **do**

$c[0, b] \leftarrow 0$

**for**  $i \leftarrow 1$  **to**  $n$  **do**

$c[i, 0] \leftarrow 0$

**for**  $i \leftarrow 1$  **to**  $n$  **do**

**for**  $b \leftarrow 1$  **to**  $B$  **do**

**if**  $x_i \leq b$  **then**

$c[i, b] \leftarrow \text{Max}\{x_i + c[i-1, b-x_i], c[i-1, b]\}$

**else**

$c[i, b] \leftarrow c[i-1, b]$

**return**  $c[n, B]$

# Finding an Optimal Subset

## SOLUTION-SUBSET-SUM (x, b, B, c)

$i \leftarrow n$

$b \leftarrow B$

$N \leftarrow \emptyset$

**while**  $i > 0$  **do**

**if**  $c[i, b] = c[i-1, b]$  **then**

$i \leftarrow i - 1$

**else**

$N \leftarrow N \cup \{x_i\}$

$i \leftarrow i - 1$

$b \leftarrow b - x_i$

**return**  $N$

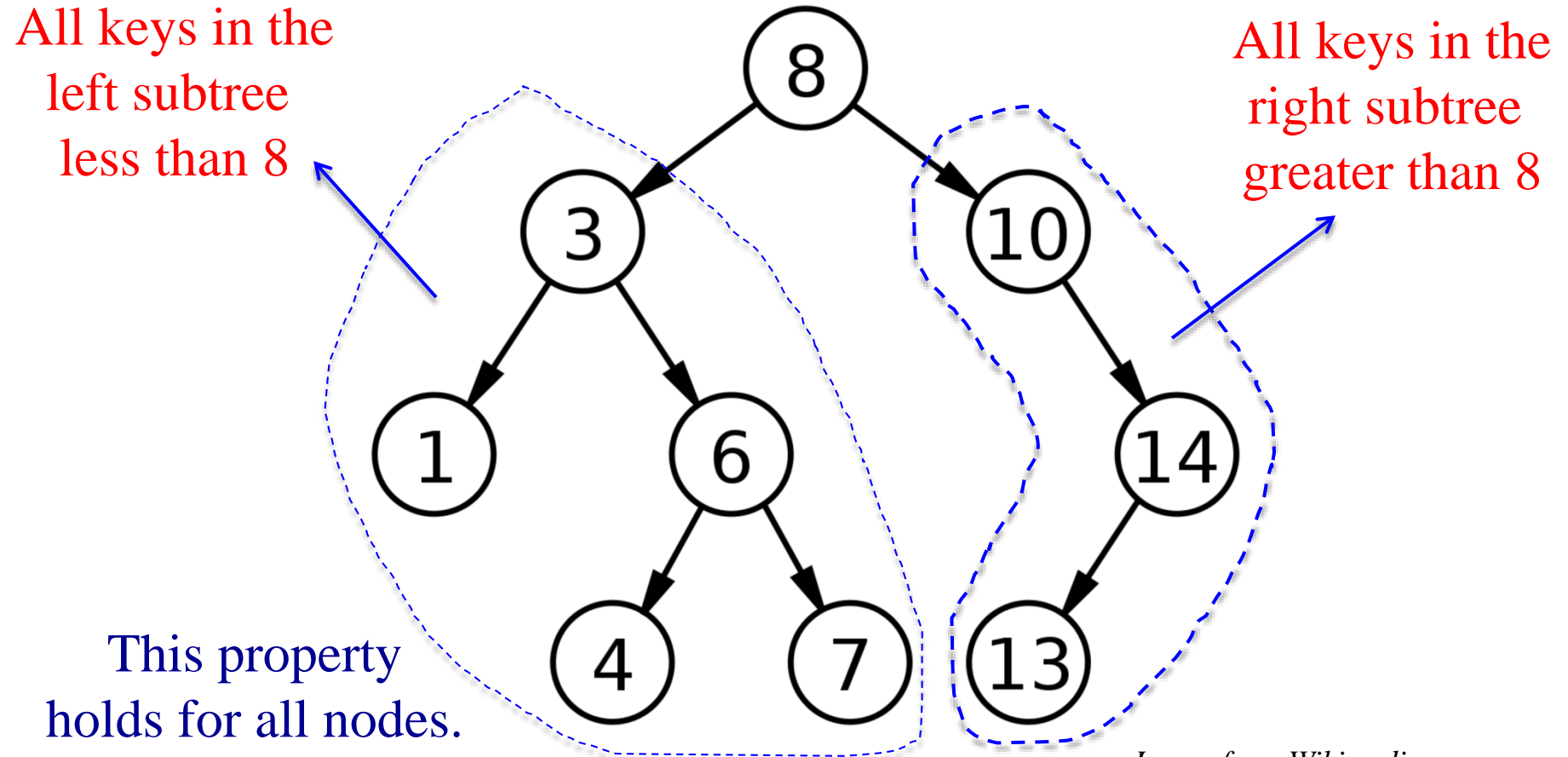
# CS473 - Algorithms I



## Problem 2

### Optimal Binary Search Tree

# Reminder: Binary Search Tree (BST)



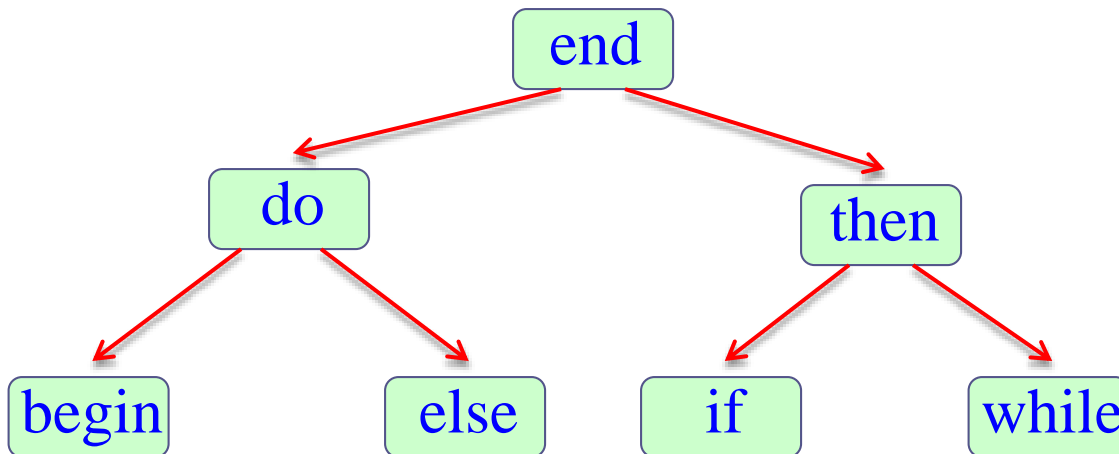
*Image from Wikimedia*

# Binary Search Tree Example

Example: English-to-French translation

Organize (English, French) word pairs in a BST

- **Keyword**: English word
- **Satellite data**: French word



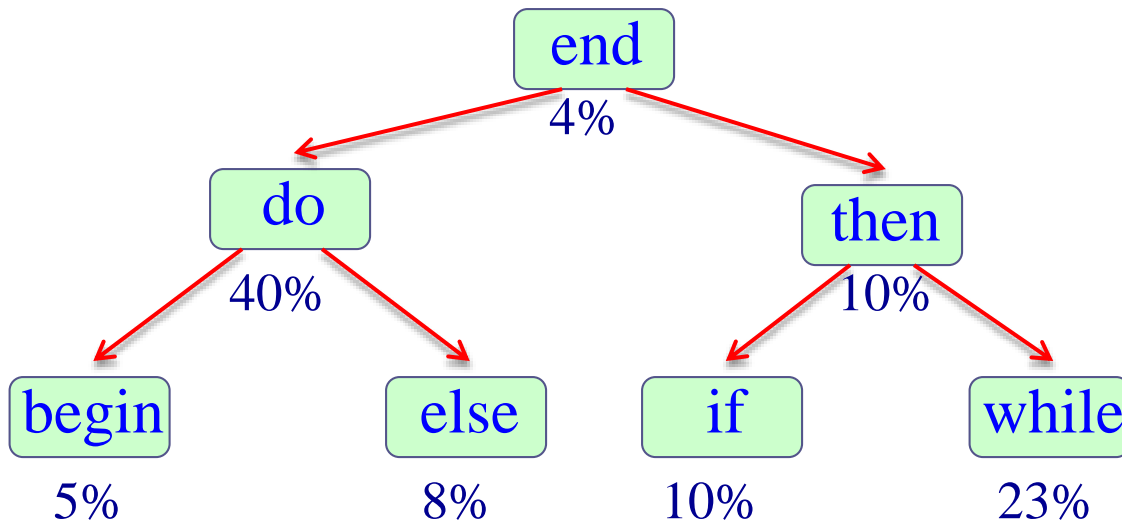
We can search for an English word (node key) efficiently, and return the corresponding French word (satellite data).



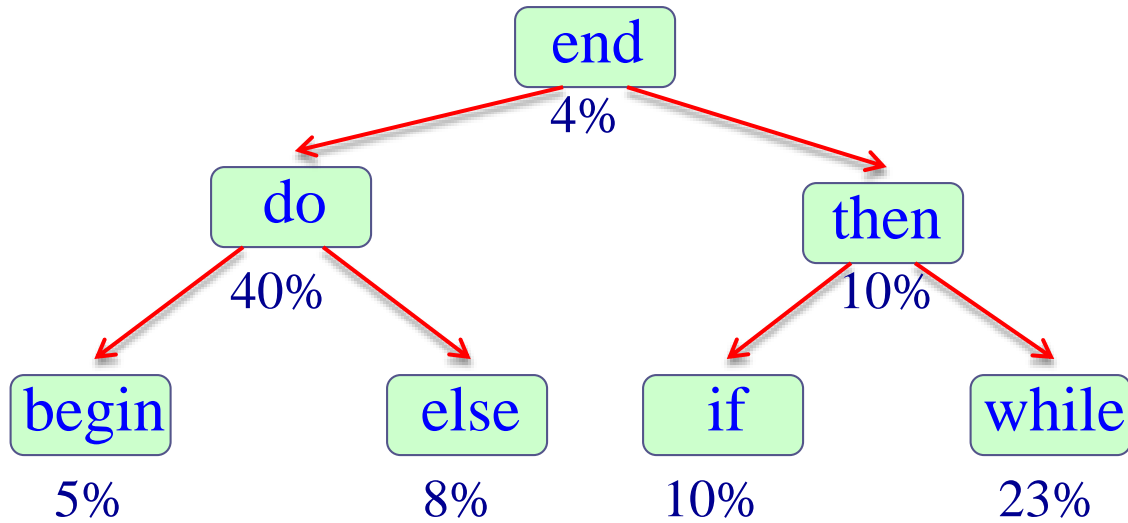
# Binary Search Tree Example

Suppose we know the frequency of each keyword in texts:

<u>begin</u>	<u>do</u>	<u>else</u>	<u>end</u>	<u>if</u>	<u>then</u>	<u>while</u>
5%	40%	8%	4%	10%	10%	23%



# Cost of a Binary Search Tree

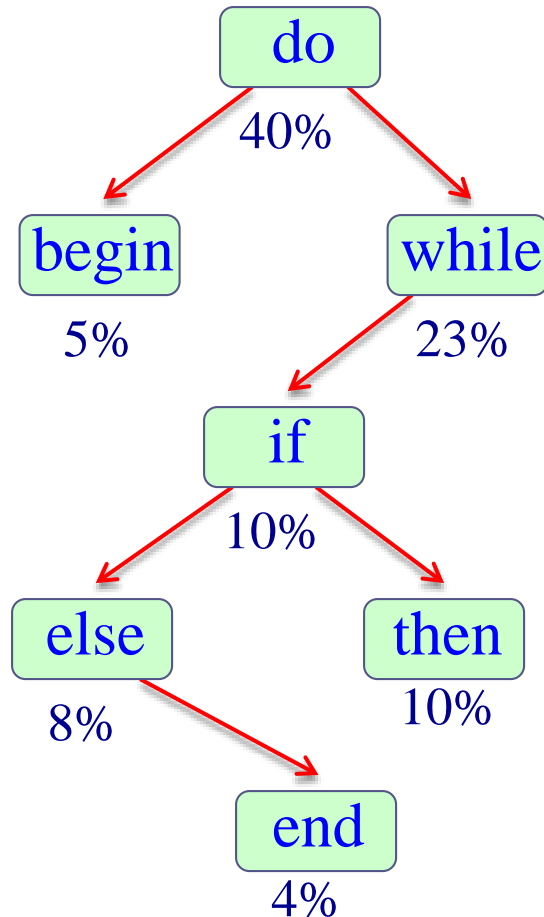


*Example:* If we search for keyword “while”, we need to access 3 nodes. So, 23% of the queries will have cost of 3.

$$\text{Total cost} = \sum_i (\text{depth}(i) + 1) \times \text{freq}(i)$$

$$= 1 \times 0.04 + 2 \times 0.4 + 2 \times 0.1 + 3 \times 0.05 + 3 \times 0.08 + 3 \times 0.1 + 3 \times 0.23$$
$$= 2.42$$

# Cost of a Binary Search Tree



A different binary search tree (BST) leads to a different total cost:

$$\begin{aligned} \text{Total cost} &= 1 \times 0.4 + 2 \times 0.05 + 2 \times 0.23 + \\ &\quad 3 \times 0.1 + 4 \times 0.08 + 4 \times 0.1 + \\ &\quad 5 \times 0.04 \\ &= 2.18 \end{aligned}$$

This is in fact an optimal BST.

# Optimal Binary Search Tree Problem

Given:

A collection of  $n$  keys  $K_1 < K_2 < \dots < K_n$  to be stored in a BST.

The corresponding  $p_i$  values for  $1 \leq i \leq n$

$p_i$ : probability of searching for key  $K_i$

Find:

An **optimal BST** with minimum total cost:

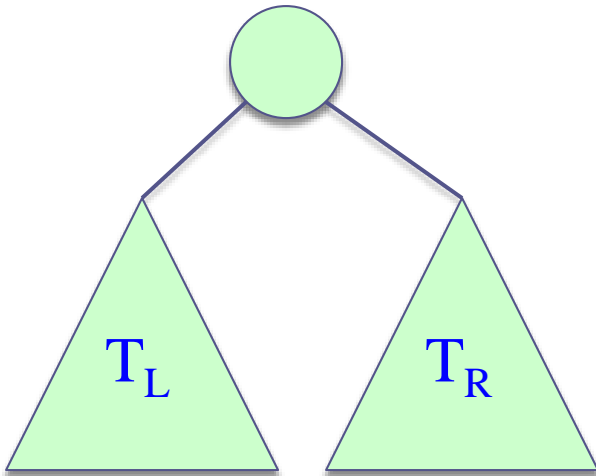
$$\text{Total cost} = \sum_i (\text{depth}(i) + 1) \times \text{freq}(i)$$

Note: The BST will be static. Only search operations will be performed. No insert, no delete, etc.

# Cost of a Binary Search Tree

**Lemma 1**: Let  $T_{ij}$  be a BST containing keys  $K_i < K_{i+1} < \dots < K_j$ . Let  $T_L$  and  $T_R$  be the left and right subtrees of  $T$ . Then we have:

$$\text{cost}(T_{ij}) = \text{cost}(T_L) + \text{cost}(T_R) + \sum_{h=i}^j p_h$$



**Intuition**: When we add the root node, the depth of each node in  $T_L$  and  $T_R$  increases by 1. So, the cost of node  $h$  increases by  $p_h$ . In addition, the cost of root node  $r$  is  $p_r$ . That's why, we have the last term at the end of the formula above.

# Optimal Substructure Property

## Lemma 2: Optimal substructure property

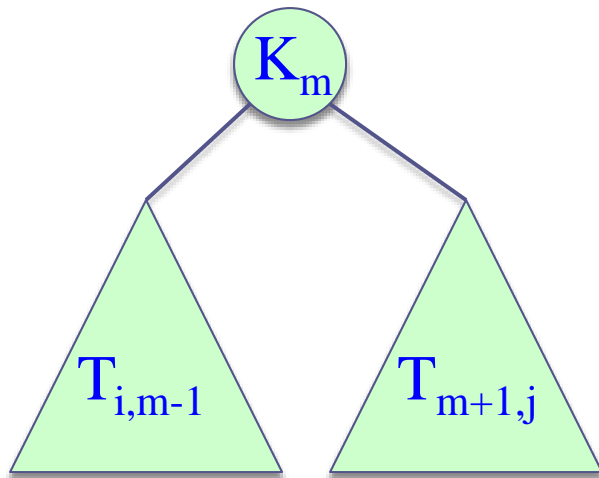
Consider an optimal BST  $T_{ij}$  for keys  $K_i < K_{i+1} < \dots < K_j$

Let  $K_m$  be the key at the root of  $T_{ij}$

Then:

$T_{i,m-1}$  is an optimal BST for subproblem containing keys:  $K_i < \dots < K_{m-1}$

$T_{m+1,j}$  is an optimal BST for subproblem containing keys:  $K_{m+1} < \dots < K_j$



$$\text{cost}(T_{ij}) = \text{cost}(T_{i,m-1}) + \text{cost}(T_{m+1,j}) + \sum_{h=i}^j p_h$$

# Recursive Formulation

*Note: We don't know which root vertex leads to the minimum total cost. So, we need to try each vertex  $m$ , and choose the one with minimum total cost.*

$c[i, j]$ : cost of an optimal BST  $T_{ij}$  for the subproblem  $K_i < \dots < K_j$

$$c[i, j] = \begin{cases} 0 & \text{if } i > j \\ \min_{i \leq r \leq j} \{c[i, r-1] + c[r+1, j] + P_{ij}\} & \text{otherwise} \end{cases}$$

$$\text{where } P_{ij} = \sum_{h=i}^j P_h$$

# Bottom-up computation

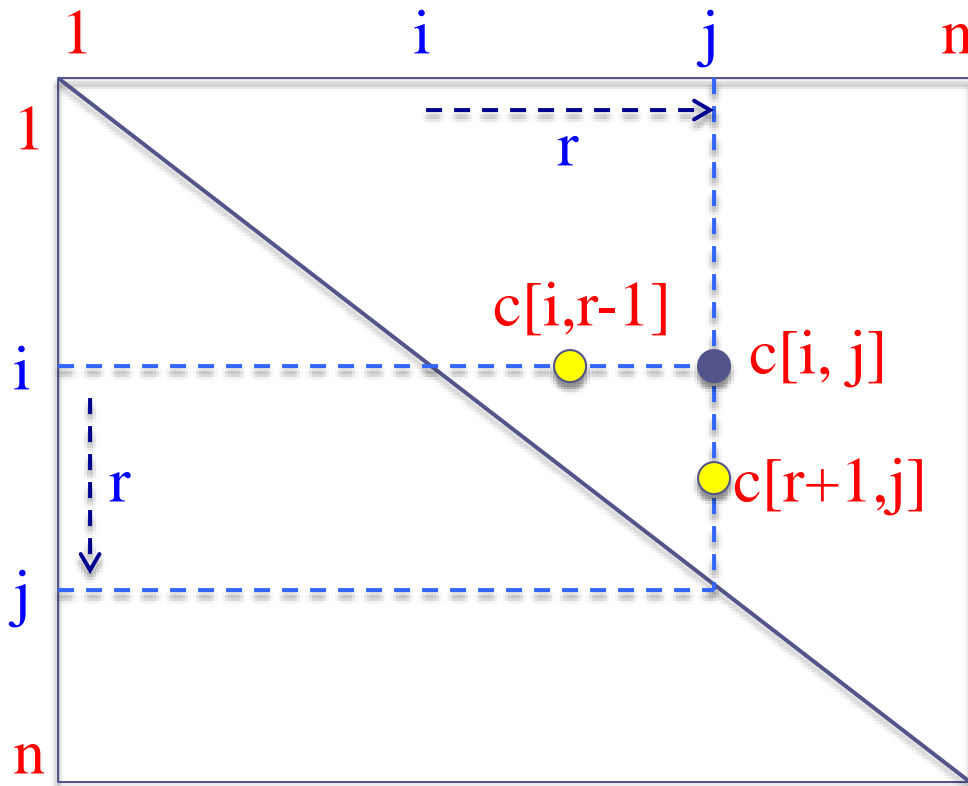
$$c[i, j] = \begin{cases} 0 & \text{if } i > j \\ \min_{i \leq r \leq j} \{c[i, r-1] + c[r+1, j] + P_{ij}\} & \text{otherwise} \end{cases}$$

How to choose the order in which we process  $c[i, j]$  values?

Before computing  $c[i, j]$ , we have to make sure that the values for  $c[i, r-1]$  and  $c[r+1, j]$  have been computed for all  $r$ .

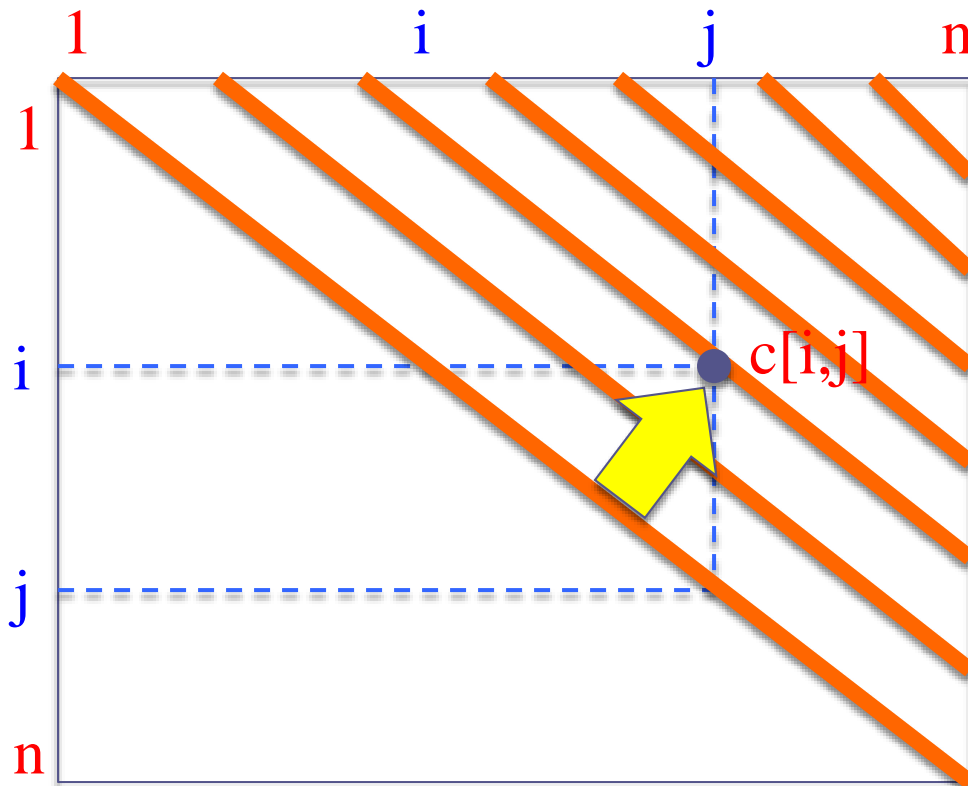


$$c[i, j] = \begin{cases} 0 & \text{if } i > j \\ \min_{i \leq r \leq j} \{c[i, r-1] + c[r+1, j] + P_{ij}\} & \text{otherwise} \end{cases}$$



$c[i, j]$  must be processed after  $c[i, r-1]$  and  $c[r+1, j]$

$$c[i, j] = \begin{cases} 0 & \text{if } i > j \\ \min_{i \leq r \leq j} \{c[i, r-1] + c[r+1, j] + P_{ij}\} & \text{otherwise} \end{cases}$$



If the entries  $c[i, j]$  are computed in the shown order, then  $c[i, r-1]$  and  $c[r+1, j]$  values are guaranteed to be computed before  $c[i, j]$ .

# Computing the Optimal BST Cost

## COMPUTE-OPTIMAL-BST-COST ( $p, n$ )

**for**  $i \leftarrow 1$  **to**  $n+1$  **do**

$c[i, i-1] \leftarrow 0$

$PS[1] \leftarrow p[1]$  //  $PS[i]$ : *prefix\_sum(i): Sum of all  $p[j]$  values for  $j \leq i$*

**for**  $i \leftarrow 2$  **to**  $n$  **do**

$PS[i] \leftarrow p[i] + PS[i-1]$  // *compute the prefix sum*

**for**  $d \leftarrow 0$  **to**  $n-1$  **do**

**for**  $i \leftarrow 1$  **to**  $n - d$  **do**

$j \leftarrow i + d$

$c[i, j] \leftarrow \infty$

**for**  $r \leftarrow i$  **to**  $j$  **do**

$c[i, j] \leftarrow \min\{c[i, j], c[i, r-1] + c[r+1, j] + PS[j] - PS[i-1]\}$

**return**  $c[1, n]$

# Note on Prefix Sum

- We need  $P_{ij}$  values for each  $i, j$  ( $1 \leq i \leq n$  and  $1 \leq j \leq n$ ),

$$\text{where: } P_{ij} = \sum_{h=i}^j p_h$$

- If we compute the summation directly for every  $(i, j)$  pair, the total runtime would be  $\Theta(n^3)$ .
- Instead, we spend  $O(n)$  time in preprocessing to compute the prefix sum array  $PS$ . Then we can compute each  $P_{ij}$  in  $O(1)$  time using  $PS$ .

# Note on Prefix Sum

In preprocessing, compute for each  $i$ :

$PS[i]$ : the sum of  $p[j]$  values for  $1 \leq j \leq i$

Then, we can compute  $P_{ij}$  in  $O(1)$  time as follows:

$$P_{ij} = PS[i] - PS[j-1]$$

Example:

	1	2	3	4	5	6	7	8
p:	0.05	0.02	0.06	0.07	0.20	0.05	0.08	0.02
PS:	0.05	0.07	0.13	0.20	0.40	0.45	0.53	0.55

$$P_{27} = PS[7] - PS[1] = 0.53 - 0.05 = 0.48$$

$$P_{36} = PS[6] - PS[2] = 0.45 - 0.07 = 0.38$$