

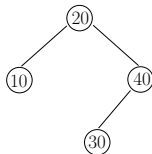
# Dynamic Programming 2: Optimal BST

Yufei Tao

Department of Computer Science and Engineering  
Chinese University of Hong Kong

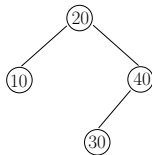
Designing a dynamic programming algorithm, in general, requires discovering a **recursive structure** of the underlying problem. Next, we will illustrate this through the **optimal BST problem**.

## Review: Binary Search Tree (BST)



- Each node stores a **key**.
- The key of an internal node  $u$  is **larger** than any key in its **left** subtree, and **smaller** than any key in its **right** subtree.

## Review: Binary Search Tree (BST)



- The **level** of a node  $u$  in a BST  $T$  — denoted as  $level_T(u)$  — equals the number of edges on the path from the root to  $u$ .
  - The level of the root is 0.
- The **depth** of a tree is the maximum level of the nodes in the tree.
- Searching for a node  $u$  incurs cost proportional to  $1 + level_T(u)$ .
  - How many nodes do you need to access to search for node 10, 20, 30, and 40, respectively?

Let  $S$  be a set of  $n$  integers.

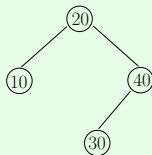
We know that a balanced BST on  $S$  has depth  $O(\log n)$ .

This is good if we assume that all the integers in  $S$  are searched with **equal probabilities**.

In practice, not all keys are equally important: some are searched **more often than others**. This gives rise to an interesting question:

If we know the search frequencies of the integers in  $S$ , how to build a better BST to minimize the average search cost?

## Example:



Suppose that we know the frequencies of 10, 20, 30, and 40 are 40%, 15%, 35%, and 10%, respectively. Then, the average cost of searching for a key in the BST equals:

$$\begin{aligned} & \text{freq}(10) \cdot \text{cost}(10) + \text{freq}(20) \cdot \text{cost}(20) + \\ & \text{freq}(30) \cdot \text{cost}(30) + \text{freq}(40) \cdot \text{cost}(40) \\ = & 40\% \cdot 2 + 15\% \cdot 1 + 35\% \cdot 3 + 10\% \cdot 2 \\ = & 2.2 \end{aligned}$$

where  $\text{freq}(k)$  denotes the search frequency of key  $k$ , and  $\text{cost}(k)$  denotes the cost of searching for  $k$  in the tree.

## The Optimal BST Problem

### Input:

- A set  $S$  of  $n$  integers:  $\{1, 2, \dots, n\}$ ;
- An array  $W$  where  $W[i]$  ( $1 \leq i \leq n$ ) stores a positive integer weight.

### Output:

A BST  $T$  on  $S$  with the smallest **average cost**:

$$\text{avgcost}(T) = \sum_{i=1}^n W[i] \cdot \text{cost}_T(i).$$

where  $\text{cost}_T(i) = 1 + \text{level}_T(i)$  is the number of nodes accessed to find the key  $i$  in  $T$ .

**Think:** here we consider that the keys are  $1, 2, \dots, n$ , respectively; do we lose any generality?

## A Slightly More General Problem

We will solve a more general version of the problem.

### Input:

- $S$  and  $W$  same as before;
- Integers  $a, b$  satisfying  $1 \leq a \leq b \leq n$ .

### Output:

A BST  $T$  on  $\{a, a + 1, \dots, b\}$  with the smallest **average cost**:

$$\text{avgcost}(T) = \sum_{i=a}^b W[i] \cdot \text{cost}_T(i).$$

where  $\text{cost}_T(i) = 1 + \text{level}_T(i)$  is the number of nodes accessed to find the key  $i$  in  $T$ .



As mentioned, an important step in designing a dynamic programming algorithm is to figure out the **recursive structure** of the underlying problem. Typically, this involves three steps:

- 1 identify **all** the possible options for the “**first**” choice;
- 2 **conditioned on** the first choice, find the optimal solution;
- 3 take the first choice that leads to the **overall best** solution.

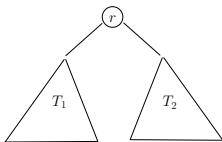
Next, we will explain how to do so for the optimal BST problem.

## 1. Find all the Options for the First Choice

**First Choice:** Key at the root of  $T$ ?

Clearly, we have  $b - a + 1$  options: we can put  $a, a + 1, \dots, \text{or } b$  as the key at the root.

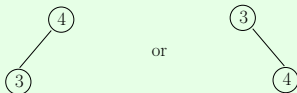
Suppose that we put  $r$  as the key at the root for some  $r \in [a, b]$ . Then, its left subtree must be a BST  $T_1$  on  $S_1 = \{a, \dots, r - 1\}$ , and its right subtree must be a BST  $T_2$  on  $S_2 = \{r + 1, \dots, b\}$ .



**Example:**  $S = \{1, 2, 3, 4\}$ ;  $W = (40, 15, 35, 10)$ .

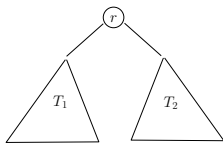
Consider the option of putting 2 at the root. The left subtree must contain just a single leaf with the key 1.

The right subtree, on the other hand, has two choices:



## 2. Conditioned on the First Choice, Find the Optimal Solution:

Put  $r$  at the root of  $T$ . Next, we will show that, to minimize the average cost of  $T$ , we should choose the best trees for  $T_1$  and  $T_2$ .



$$\begin{aligned} & \text{avgcost}(T) \\ &= \sum_{i=a}^b W[i] \cdot \text{cost}_T(i) = \sum_{i=a}^b W[i] \cdot (1 + \text{level}_T(i)) \\ &= \left( \sum_{i=a}^b W[i] \right) + \sum_{i=a}^b W[i] \cdot \text{level}_T(i) \\ &= \left( \sum_{i=a}^b W[i] \right) + \left( \sum_{i=a}^{r-1} W[i] \cdot \text{level}_T(i) \right) + \left( \sum_{i=r+1}^b W[i] \cdot \text{level}_T(i) \right) \end{aligned}$$

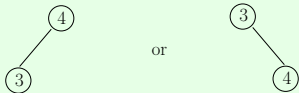
(Continuing on the next slide)

$$\begin{aligned}
&= \left( \sum_{i=a}^b W[i] \right) + \left( \sum_{i=a}^{r-1} W[i] \cdot (1 + \text{level}_{T_1}(i)) \right) + \\
&\quad \left( \sum_{i=r+1}^b W[i] \cdot (1 + \text{level}_{T_2}(i)) \right) \\
&= \left( \sum_{i=a}^b W[i] \right) + \left( \sum_{i=a}^{r-1} W[i] \cdot \text{cost}_{T_1}(i) \right) + \left( \sum_{i=r+1}^b W[i] \cdot \text{cost}_{T_2}(i) \right) \\
&= \left( \sum_{i=a}^b W[i] \right) + \text{avgcost}(T_1) + \text{avgcost}(T_2)
\end{aligned}$$

Clearly, we should minimize  $\text{avgcost}(T_1)$  and  $\text{avgcost}(T_2)$ , namely, building optimal BSTs on  $S_1$  and  $S_2$ , recursively.

**Example:**  $S = \{1, 2, 3, 4\}$ ;  $W = (40, 15, 35, 10)$ .

Consider the option of putting 2 at the root. As mentioned, the right subtree has two choices:



We know from the above discussion that the right subtree should be an optimal BST on  $\{3, 4\}$ . Which of the above two choices is optimal on  $\{3, 4\}$ ?

The answer is the second one: it has an average cost of  $35 \cdot 1 + 10 \cdot 2 = 55$ .

Define  $optavg(a, b)$  as

- 0, if  $a > b$ ;
- the smallest average cost of a BST on  $\{a, a + 1, \dots, b\}$ , otherwise.

Define  $optavg(a, b | r)$  as the optimal average cost of a BST, **on condition that** the BST has  $r$  as the key of the root.

The previous discussion has essentially proved:

$$\begin{aligned} & optavg(a, b | r) \\ = & \left( \sum_{i=a}^b W[i] \right) + optavg(a, r - 1) + optavg(r + 1, b). \end{aligned}$$

**Example:**  $S = \{1, 2, 3, 4\}$ ;  $W = (40, 15, 35, 10)$ .

Consider the option of putting 2 at the root.

$$\begin{aligned} & \text{optavg}(1, 4 \mid 2) \\ &= \left( \sum_{i=1}^4 W[i] \right) + \text{optavg}(1, 1) + \text{optavg}(3, 4) \\ &= 100 + 40 + 55 = 195. \end{aligned}$$

Hence, **if we want to put 2 at the root**, the best BST we can construct has average cost 195.



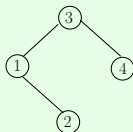
**3. Selecting the Best First Choice:** The best choice for  $r$  is the one that leads to the smallest average cost, namely:

$$\begin{aligned} & \text{optavg}(a, b) \\ = & \min_{r=a}^b \text{optavg}(a, b \mid r) \\ = & \left( \sum_{i=a}^b W[i] \right) + \min_{r=a}^b \left\{ \text{optavg}(a, r-1) + \text{optavg}(r+1, b) \right\}. \end{aligned}$$

This is the recursive structure of the problem.

**Example:**  $S = \{1, 2, 3, 4\}$ ;  $W = (40, 15, 35, 10)$ .

The optimal tree is actually:



$$\begin{aligned} \text{optavg}(1, 4) &= \text{optavg}(1, 4 \mid 3) \\ &= \left( \sum_{i=1}^4 W[i] \right) + \text{optavg}(1, 2) + \text{optavg}(4, 4) \\ &= 100 + \text{optavg}(1, 2) + 10 = 110 + \text{optavg}(1, 2) \\ &= 110 + \text{optavg}(1, 2 \mid 1) \\ &= 110 + \left( \sum_{i=1}^2 W[i] \right) + \text{optavg}(1, 0) + \text{optavg}(2, 2) \\ &= 110 + 55 + 0 + 15 = 180. \end{aligned}$$

## Putting Everything Together

We have converted the optimal BST problem into the following problem:

**Input:** An array  $W$  of  $n$  integers.

**Output** Compute  $optavg(1, n)$  where for any  $a, b \in [1, n]$ :

$$optavg(a, b) = \begin{cases} 0, & \text{if } a > b \\ \left( \sum_{i=a}^b W[i] \right) + \min_{r=a}^b \left\{ optavg(a, r-1) + optavg(r+1, b) \right\} & \text{otherwise} \end{cases}$$

This is precisely the problem we studied in the previous lecture! Recall that with dynamic programming, we can compute  $optavg(1, n)$  in  $O(n^3)$  time.

Strictly speaking, there is one more step: although we have calculated  $optavg(1, n)$ , we still have not produced the optimal BST yet!

This is, in fact, rather trivial — you can do so in  $O(n)$  time after computing  $optavg(1, n)$  with dynamic programming. This will be left as a regular exercise.