Binary Search Trees CS 624 — Analysis of Algorithms

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07 Binary Search Trees

For the next few slides, "graph" means "undirected graph".1

### Definitions (Path, Simple Path)

A **path** in a graph is a sequence  $v_0, v_1, v_2, \ldots, v_n$  where each  $v_j$  is a vertex in the graph and where each  $v_i$  and  $v_{i+1}$  are joined by an edge. The **length** of the path  $v_0, v_1, v_2, \ldots, v_n$  is *n*. A path can have length 0. A path in a graph is **simple** iff it contains no vertex more than once.

Usually we write  $v_0 
ightarrow v_1 
ightarrow v_2 
ightarrow ... 
ightarrow v_n$  to denote a path.

<sup>1</sup>See also Appendix B.4 (Graphs) and B.5 (Trees) in the textbook.

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# Definitions (Loop, Simple Loop)

A **loop**<sup>2</sup> is a path with at least one edge that begins and ends at the same vertex.

A loop  $v_0 
ightarrow v_1 
ightarrow v_2 
ightarrow ... 
ightarrow v_k$  is simple iff

- 1.  $k \geq 3$  (that is, there are at least 4 vertices on the path), and
- 2. it contains no vertex more than once, except of course for the first and last vertices,  $v_0 = v_k$ , and
- 3. that (first and last) vertex occurs exactly twice

The definition of simple loop excludes trivial loops like  $v_0 \rightarrow v_1 \rightarrow v_0$ and  $v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow v_1 \rightarrow v_0$ .

<sup>&</sup>lt;sup>2</sup>The textbook calls this a cycle.

Definition (Tree)

A tree is a undirected graph that contains no simple loops.

## Definition (Rooted Tree)

A rooted tree is a tree with a distinguished vertex called the root.

### Definitions (Ancestor, Descendant, Parent, Child)

Let T be a rooted tree with root r, and let x and y be vertices in T (and either or both of them might be r).

- If there is a simple path from r through x to y, we say that x is an ancestor of y and y is a descendant of x.
- Furthermore, if the part of the path from x to y consists of exactly one edge, we say that x is the parent of y and y is a child of x.

Note that a vertex is both an ancestor and a descendant of itself. But a vertex cannot be its own parent.

# **Binary Trees**

### Recall from Lecture 03:

## Definition (Binary Tree)

## A binary tree is either

- a node with two children, called *left* and *right*, which are also binary trees, and optionally a *data* field; or
- NIL, representing the empty tree

## Examples (Binary trees with and without data)

NIL

NIL NIL NIL NIL







### Reminder, tree traversal (any binary tree):

### preorder traversal

- 1. visit the node itself first
- 2. traverse the left child
- 3. traverse the right child

## inorder traversal

- 1. traverse the left child
- 2. visit the node itself
- 3. traverse the right child

### postorder traversal

- 1. traverse the left child
- 2. traverse the right child
- 3. visit the node itself last

# Traversal Algorithms

## Algorithm 1 Preorder-Tree-Walk(x)

- 1: if  $x \neq \text{NIL}$  then
- 2: visit(x)
- 3: Preorder-Tree-Walk(left(x))
- 4: Preorder-Tree-Walk(right(x))
- 5: end if

## Algorithm 3 Postorder-Tree-Walk(x)

- 1: if  $x \neq \text{NIL}$  then
- 2: Postorder-Tree-Walk(left(x))
- 3: Postorder-Tree-Walk(right(*x*))
- 4: visit(x)
- 5: **end if**

Algorithm 2 Inorder-Tree-Walk(x)

- 1: if  $x \neq \text{NIL}$  then
- **2:** Inorder-Tree-Walk(left(x))
- 3: visit(x)
- 4: Inorder-Tree-Walk(right(x))
- 5: end if

# Running Times of Traversal Algorithm

#### Theorem

If x is the root of a binary tree with n nodes, then each of the above traversals takes  $\Theta(n)$  time.

#### Proof.

Let us define:

- c = time for the test  $x \neq nil$
- v = time for the call to visit x
- T(k) = time for the call to traverse a tree with k nodes

#### Then certainly we have

- 1. T(0) = c and if the tree with n nodes has a right child with k nodes (so its left child must have n k 1 nodes), then
- 2. T(n) = c + T(k) + T(n k 1) + v

We can show that T(n) = (2c + v)n + c.

### Definition

A **binary search tree (BST)** is a binary tree with data including a comparison key, where every node *x* satisfies the BST properties:

- 1. If y is a node on the left of x,  $key[y] \le key[x]$ .
- 2. If y is a node on the right of x,  $key[y] \ge key[x]$ .



# Search

### **Recursive version**

## Iterative version

### Algorithm 5 TreeSearch(x, k)1: while $x \neq NIL$ and $k \neq kev[x]$ do

- 1: while  $x \neq \text{NIL}$  and  $k \neq \text{key}[x]$ 2: if k < key[x] then
- 3:  $x \leftarrow \operatorname{left}[x]$
- 4: **else**
- 5:  $x \leftarrow \operatorname{right}[x]$
- 6: end if
- 7: end while
- 8: **return** *x*

The running time is O(h), where h is the height of the tree.

Algorithm 6 TreeMinimum(x)	Algorithm 7 TreeMaximum(x)
1: while $\operatorname{left}[x] \neq NIL$ do	1: while $\operatorname{right}[x] \neq NIL \operatorname{do}$
2: $x \leftarrow \operatorname{left}[x]$	2: $x \leftarrow \operatorname{right}[x]$
3: end while	3: end while
4: <b>return</b> x	4: return x

The running time is O(h), where h is the height of the tree.

### Algorithm 8 TreeSuccessor(x)

- 1: if  $right[x] \neq NIL$  then
- **2:** return TreeMinimum(right[x])
- 3: end if

```
4: y \leftarrow \text{parent}[x]

5: while y \neq \text{NIL} and x = \text{right}[y] do

6: x \leftarrow y

7: y \leftarrow \text{parent}[x]
```

- 8: end while
- 9: **return** *y* 
  - The running time of TreeSuccessor on a tree of height h is again O(h), since the algorithm consists on following a path from a node to its successor, and the maximum path length is h.
  - What happens when we apply this procedure to the node in the figure above whose key is 20?

## TreePredecessor runs in a similar fashion with a similar running time.

#### Theorem

The dynamic-set operations Search, Minimum, Maximum, Successor, and Predecessor can be made to run in O(h) time on a binary search tree of height h.

# Insert

### Algorithm 9 TreeInsert(T, z)

```
1: v \leftarrow NIL
 2: x \leftarrow \operatorname{Root}[T]
 3: while x \neq NIL do
 4:
      v \leftarrow x
 5:
       if key[z] < key[x] then
 6:
             x \leftarrow \text{left}[x]
 7:
       else
8:
             x \leftarrow \operatorname{right}[x]
 9:
         end if
10: end while
11: parent[z] \leftarrow v
12: if y == NIL /* only if T was empty */ then
         \operatorname{Root}[T] \leftarrow z
13:
14: else if key[z] < key[y] then
15:
         left[v] \leftarrow z
16: else
         \operatorname{right}[y] \leftarrow z
17:
18: end if
```

#### Lines 1–10:

- x is the "lead explorer", for where z ought to be
- y lags behind by one step
- when x becomes NIL, y is the last node on the path to z's destination (if non-empty)

Lines 11–18:

▶ insert *z* into the tree at "*x*"

# Insert Example



Operations on BSTs

### Obviously, Insert runs in O(h) time on a tree of height h

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Deleting a node is more complicated.

If the node is buried within the tree, we will have to move some of the other nodes around.

- ▶ There are three cases to consider when deleting a node *d*:
  - 1. d is a leaf
  - 2. *d* has one child
  - 3. d has two children

# **Delete Examples**



- Case I d is a leaf. This case is trivial. Just delete the node. This amounts to figuring out which child it is of its parent, and making the corresponding child pointer nil.
- Case II: d has one child. In this case, delete d and "splice" its child to its parent – that is, make the parent's child pointer that formerly pointed to d now point to d's child, and make that child's parent pointer now point to d's parent.
- Case III: d has two children. In this case we can't simply move one of the children of d into the position of d. What we need to do is find d's successor and replace d with it. Then delete d's successor. Since the successor has at most one child (why?) then we revert to case I or II.

An algorithm for building a binary search tree from an array A[1 .. n]:

# Algorithm 10 $\operatorname{BuildBST}(A)$

- 1:  $T \leftarrow \mathsf{Create}\;\mathsf{Empty}\;\mathsf{Tree}$
- 2: for  $i \leftarrow 1$  to n do
- 3: TreeInsert(T, A[i])

4: end for

- What is the running time?
- Worst case: array already sorted, quadratic
- **•** Best case: looks like  $O(n \log n)$
- What does it remind us of?

▶  $pivot \leftarrow A[p]$ 

- Let L be the sequence of elements of A[p + 1 .. q] that are less than the pivot, in the order they appear in A
- Let U be the sequence of elements of A[p + 1 .. q] that are greater than pivot, in the order they appear in A
- Rearrange the elements in A[p ... q] so that they appear like this:

# $L \ pivot \ U$

This may require more time than the original partition but not asymptotically more.

- Show that the comparisons needed to build a BST from an array A[1..n] are exactly the same comparisons needed to do quicksort on the array, using ModifiedPartition.
- Hint: The comparisons in quicksort are against the pivot elements and the successive pivot elements are the successive elements added to the BST.

# Running Time for Constructing a BST

- We know that the average time for quicksort is  $\Theta(nlogn)$ .
- What is the "average time" for building a BST?
- It is the average over all possible permutations of the input array.
- > This is exactly what we get with randomized quicksort.

### Theorem

The average time for constructing a BST is  $\Theta(nlogn)$ .

- > The average search time in a BST is h, the height of a tree.
- What is the average height of a BST?
- We know the search time is the depth of a node.
- Which is the number of comparisons we make when inserting the node into the tree.

- We see that the total expected number of comparisons is  $O(n \log n)$ .
- So the average number of comparisons is  $O(\log n)$  per node.
- The average cost for search in a randomly build BST is therefore O(log n).
- ► There may be longer paths in a linear tree the average search time is O(n).
- However, the average height of a randomly build BST is  $O(\log n)$ .

# Running Time for Searching a BST

- Let X<sub>n</sub> be a random variable whose value is the height of a binary search tree on n keys
- Let  $P_n$  be the set of all permutations of those n keys. (So the number of elements of  $P_n$  is n!)
- Let  $\pi$  to denote a permutation in  $P_n$ .  $X_n$  is actually a function on  $P_n$ .
- Its value  $X_n(\pi)$  when applied to a permutation  $\pi \in P_n$  is the height of the binary search tree built from that permutation  $\pi$
- We want to find  $E(X_n)$ , the *expectation* of  $X_n$ .
- ► This is by definition  $\sum_{\pi \in P_n} p(\pi) X_n(\pi)$  where  $p(\pi)$  denotes the probability of the permutation  $\pi$ .
- Assuming that all permutations have equal probability,  $p(\pi) = \frac{1}{n!}$  for all  $\pi$ , and so  $E(X_n) = \frac{1}{n!} \sum_{\pi \in P_n} X_n(\pi)$

# Note on Distribution

If A and B are two random variables on the same space  $P_n$ , then

$$\begin{split} E(A+B) &= \sum_{\pi \in P_n} p(\pi) \big( A(\pi) + B(\pi) \big) \\ &= \sum_{\pi \in P_n} p(\pi) A(\pi) + \sum_{\pi \in P_n} p(\pi) B(\pi) \\ &= E(A) + E(B) \end{split}$$

Note that  $\max\{A, B\}$  is also a random variable on  $P_n$  – its value at  $\pi$  is just  $\max\{A(\pi), B(\pi)\}$ . And we have the useful inequality

$$egin{aligned} &Eig(\max\{A,B\}ig) = \sum_{\pi\in P_n} p(\pi) \maxig\{A(\pi),B(\pi)ig\} \ &\leq \sum_{\pi\in P_n} p(\pi)ig(A(\pi)+B(\pi)ig) \ &= E(A+B) = E(A) + E(B) \end{aligned}$$

- Consider a permutation  $\pi$ . The root of the tree will be the first element of  $\pi$ .
- Suppose the root has position k in the sorted list of keys.
- That means that there will be k 1 keys less than it and n k keys greater than it.
- So the left subtree will have k 1 elements and the right subtree will have n k elements.
- Those elements are also chosen randomly from sets of size k 1 and n k respectively, so we have

$$X_n(\pi) = 1 + \max\{X_{k-1}(\pi), X_{n-k}(\pi)\}$$

This is our fundamental recursion.

Since each value of k is chosen with the same probability (that probability being  $\frac{1}{n}$ ), we have  $E(X_n) = \sum_{n=1}^{n} \frac{1}{2} E(1 + \max\{X_{k-1}, X_{n-k}\})$ 

$$\sum_{k=1}^{n-1} n^{-1} (1 + \dots + (1 + \dots + n))$$

- An effective way to estimate it would be to set  $Y_n = 2^{X_n}$ .
- So  $Y_n$  is itself a random variable defined on the set P whose value on the permutation  $\pi$  is  $Y_n(\pi) = 2^{X_n(\pi)}$
- At first there is no intuitive significance to the reason for doing this. It's just that we can do better with the mathematics that way.
- Compute  $E(Y_n)$  and use this to get a bound on  $E(X_n)$ .
- This step is also somewhat tricky if you haven't seen it before, but it is a general technique.

$$\begin{split} Y_n(\pi) &= 2^{X_n(\pi)} = 2^{1 + \max\{X_{k-1}(\pi), X_{n-k}(\pi)\}} \\ &= 2 \cdot 2^{\max\{X_{k-1}(\pi), X_{n-k}(\pi)\}} = 2 \cdot \max\{2^{X_{k-1}(\pi)}, 2^{X_{n-k}(\pi)}\} \\ &= 2 \cdot \max\{Y_{k-1}(\pi), Y_{n-k}(\pi)\} \end{split}$$

Since each value of k is chosen with probability  $\frac{1}{n}$ :

$$egin{aligned} E(Y_n) &= \sum_{k=1}^n rac{1}{n} \cdot 2Eig( \max\{Y_{k-1},Y_{n-k}\}ig) = rac{2}{n} \sum_{k=1}^n Eig( \max\{Y_{k-1},Y_{n-k}\}ig) \ &\leq rac{2}{n} \sum_{k=1}^n ig( E(Y_{k-1}) + E(Y_{n-k})ig) \end{aligned}$$

Each term is counted twice so we can simplify to get this:

$$E(Y_n) \leq rac{4}{n} \sum_{k=1}^n E(Y_{k-1}) = rac{4}{n} \sum_{k=0}^{n-1} E(Y_k)$$

It is more convenient to use a strict equality, rather than an inequality. It turns out that we can assume this to be the case since we're really only concerned with an upper bound.

#### Lemma

If f and g are two functions such that

$$f(0) = g(0)$$
 (1)  
 $f(n) \le rac{4}{n} \sum_{k=0}^{n-1} f(k)$  (2)  
 $g(n) = rac{4}{n} \sum_{k=0}^{n-1} g(k)$  (3)

then  $f(k) \leq g(k)$  for all  $k \geq 1$ .

### Proof.

We'll prove this by induction. The inductive hypothesis is that  $f(k) \leq g(k)$  for all k < n. We know that this statement is true for n = 1 by the equation above. The inductive step is then to show that this statement remains true for k = n. To show this, we just compute as follows:

$$egin{aligned} f(n) &\leq rac{4}{n} \sum_{k=0}^{n-1} f(k) \ &\leq rac{4}{n} \sum_{k=0}^{n-1} g(k) = g(n) \end{aligned}$$

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- ▶ Based on this, we can assume that  $E(Y_n) = \frac{4}{n} \sum_{k=0}^{n-1} E(Y_k)$ .
- ▶ because any upper bound we obtain for  $E(Y_n)$  from this identity will also be an upper bound for the "real"  $E(Y_n)$ .
- This is a similar trick to the one we used in deriving the average case running time of Quicksort.
- We can do something very similar here, although it is a little more complicated:

• 
$$E(Y_{n+1}) = \frac{4}{n+1} \sum_{k=0}^{n} E(Y_k)$$
 and  $E(Y_n) = \frac{4}{n} \sum_{k=0}^{n-1} E(Y_k)$ 

We get rid of the denominators:

• 
$$(n+1)E(Y_{n+1}) = 4\sum_{k=0}^{n} E(Y_k)$$

$$\blacktriangleright nE(Y_n) = 4 \sum_{k=0} E(Y_k)$$

- ▶ Now let us subtract and get:  $(n + 1)E(Y_{n+1}) nE(Y_n) = 4E(Y_n)$ ▶  $(n + 1)E(Y_{n+1}) = (n + 4)E(Y_n)$
- Divide both sides by (n + 1)(n + 4). We get  $\frac{E(Y_{n+1})}{n+4} = \frac{E(Y_n)}{n+1}$ .
- ▶ If you look at it closely for a little while, you will see that if we now divide each side by (n + 2)(n + 3), we will get something nice:  $\frac{E(Y_{n+1})}{(n+4)(n+3)(n+2)} = \frac{E(Y_n)}{(n+3)(n+2)(n+1)}$ .

- And so if we define  $g(n) = \frac{E(Y_n)}{(n+3)(n+2)(n+1)}$
- Then we have just derived the fact that g(n+1) = g(n)
- In other words, g(n) is some constant. Call it c.
- ▶ Then we have  $E(Y_n) = c(n+3)(n+2)(n+1) = O(n^3)$
- We are not done yet! We have to find  $E(X_n)$

- ▶ We know that there is a constant C > 0 and a number  $n_0 \ge 0$ such that for all  $n \ge n_0$ ,  $E(Y_n) \le Cn^3$ . Hence for all  $n \ge n_0$ ,  $2^{E(X_n)} \le E(2^{X_n}) = E(Y_n) \le Cn^3$
- ► Taking the logarithm of both sides we get  $E(X_n) \le \log_2 C + 3 \log_2 n = O(\log n)$
- In other words, the expected height of a randomly build binary search tree is O(log n).