# Searching SFWRENG 2CO3: Data Structures and Algorithms

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# Recap

 $\blacktriangleright$  Fundamental analysis of algorithms and data structures. Correctness, complexity (average, amortized, expected), recurrences, recurrence trees.

▶ Basic algorithms. LinearSearch, BinarySearch, InsertionSort, SelectionSort.

▶ Collection types. Bag, stack, queue, double-ended queue, priority queue.

▶ Data structures. Ring buffer, linked lists, dynamic arrays, trees and heaps.

 $\blacktriangleright$  Fast data analysis algorithms. MergeSort, Merge, QuickSort, Partition, Select, HeapSort. Fundamental tools in the arsenal of programmers.

Most-commonly implemented using either search trees or hash tables: vastly different classes of data structures with vastly different properties.

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Sets and CONTAINS

- $\triangleright$  We typically write  $v \in S$  instead of Contains(S, v).
- $\triangleright$  We typically write  $v \notin S$  instead of  $\neg$ Contains(S, v).
- $\triangleright$  We typically write |S| instead of Size(S).

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Sets often also support set operations such as UNION( $S_1$ ,  $S_2$ ) compute the set  $S_1 \cup S_2$ . INTERSECT( $S_1$ ,  $S_2$ ) compute the set  $S_1 \cap S_2$ . DIFFERENCE( $S_1, S_2$ ) compute the set  $S_1 \setminus S_2$ .

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 $\overline{\ }$  We will *not* focus on set operations.

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N Contains operations.  $U$  ADD operations.

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# Gering and modifying values

- $\blacktriangleright$  We typically write  $D[k]$  instead of GET(D, k).
- $\triangleright$  We typically write  $D[k] := v$  to change the value of a kv-pair in D.
- $\triangleright$  We typicaly write |D| instead of Size(D).

# A use-case for dictionaries

Algorithm WORDCOUNT(stream):

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After finding a key (e.g., Contains, GET), updating the value is typically  $\Theta$  (1).

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N - U updates to values (\Theta (1), for "free").
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To simplify presentation, we focus on the details of data structures that implement *sets*.

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CONTAINS $(S, word)$ .

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Implementation on top of a dynamic array: similarly bad.

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a just word length = 3

DELETE $(S, is)$ .

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If we maintain that sets are ordered: we can use variants of MERGE for union, intersection, and difference of sets.

### Comparing set implementations

#### Complexity of DEDUP(stream)

 $N$  Contains operations with  $N = |stream|$ .

 $U$  ADD operations with  $U$  the number of unique words in stream.

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#### Conclusion

- $\triangleright$  List implementation (doubly linked, dynamic array): practical only for tiny datasets.
- $\triangleright$  Sorted dynamic array implementation: only practical if usage of Contains dominates.

- $\blacktriangleright$  Linked lists can easily be modified due to usage of pointers.
- ▶ BINARYSEARCH can quickly find values even in huge datasets.

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Each value in a binary tree is stored in a binary tree node: value The value held by the binary tree node. left A pointer to the left child of the node, if any.

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A binary search tree is represented by a pointer to the root node. If the tree is empty, this pointer is @null.







Algorithm INORDERTRAVERSE( $n$ , action A):

**Input:**  $n$  is a pointer to a node.

- 1: if  $n.left \neq 0$  null then
- 2: INORDERTRAVERSE $(n.left, A)$ .
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Algorithm PREORDERTRAVERSE( $n$ , action A):

**Input:**  $n$  is a pointer to a node.

- 1:  $A(n)$ .
- 2: if  $n.left \neq 0$  null then
- 3: PreorderTraverse(n.left, A).
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PREORDERTRAVERSE(root, "output n.value").





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Algorithm POSTORDERTRAVERSE( $n$ , action A):

**Input:**  $n$  is a pointer to a node.

- 1: if  $n.left \neq 0$  null then
- 2: POSTORDERTRAVERSE $(n.left, A)$ .
- 3: if *n.right*  $\neq$  @null then
- 4: PostorderTraverse(n.right, A).
- 5:  $A(n)$ .



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- $\blacktriangleright$  InorderTraverse(root, A)
- $\blacktriangleright$  PREORDERTRAVERSE(root, A)
- $\blacktriangleright$  POSTORDERTRAVERSE(root, A)
## Intermezzo: Traversing binary trees



Let  $A :=$  "output *n.value*".

For readabilty, we added parentheses and commas.

- ▶ INORDERTRAVERSE(root, A)  $\rightarrow$  (12 \* 4) + (5 / 2).
- ▶ PREORDERTRAVERSE(root, A)  $\rightarrow$  +(\*(12, 4), /(5, 2)).
- ▶ POSTORDERTRAVERSE(root, A)  $\rightarrow$  12 4  $\star$  5 2 / +.

## Intermezzo: Traversing binary trees



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- ▶ INORDERTRAVERSE(root, A)  $\rightarrow$  (12 \* 4) + (5 / 2). ("daily" notation)
- ▶ PREORDERTRAVERSE(root, A)  $\rightarrow$  +(\*(12, 4), /(5, 2)).

(prefix notation: function calls)

▶ POSTORDERTRAVERSE(root, A)  $\rightarrow$  12 4  $\star$  5 2 / +.

(postfix notation)



Consider the binary search tree rooted at node n.



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How to find a value  $v$ ?

Adjust binary search to work on trees.



#### Algorithm BSTSEARCHR $(n, v)$ :

Input: *n* points to a binary search tree node.

- 1: if  $n =$  @null or *n.value* = v then
- $2:$  return  $n.$
- 3: else if n value  $\lt v$  then
- 4: return BSTSEARCHR(n.right, v).
- 5: else
- 6: return BSTSEARCHR $(n.left, v)$ .

Result: return the node that holds v

(or @null if no such node exists).



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Runtime complexity Length of path from root to a leaf.



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### Runtime complexity

Length of path from *root* to a leaf  $\rightarrow \lceil \log_2(N) \rceil$  *if* a tree with N nodes is "balanced". Balanced tree: any path from the root to a leaf has length at-most  $\lceil \log_2(N) \rceil$ .



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# Runtime complexity

Length of path from root to a leaf  $\rightarrow$  worst-case N. Challenge: Our algorithms to modify trees must assure (close to) balance.



a

A recursion-free BSTSearchR:

### Algorithm BSTSEARCH $(n, v)$ :

Input: *n* points to a binary search tree node.

- 1: while  $n \neq 0$  enull and n. value  $\neq v$  do
- 2: if *n.* value  $\lt v$  then
- 3:  $n := n$ . right.
- 4: else
- 5:  $n := n.left$ .
- 6: return  $n$ .

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#### High-level sketch: adding value v

- 1. Make a node  $m$  for value  $v$ .
- 2. Find the node that will become parent  $p$  of node  $m$ .
- 3. Based on *p. value*, add *m* as either the left or right child of  $p$ .

Find a candidate parent  $p$  to hold a node with value  $v$ 

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#### Algorithm BSTFINDPARENT $(n, v)$ :

**Input:** *n* points to a binary search tree node.

- 1:  $p := 0$  mull.
- 2: while  $n \neq \emptyset$ null do
- 3:  $p := n$ .
- 4: if n value  $\lt v$  then
- 5:  $n := n$ . right.
- 6: else
- 7:  $n := n.left$ .
- $8:$  return  $p.$

Add *m* as either the left or right child of  $p$ Let  $p := \text{BSTFINDPARENT(root, V)}$ . Let *m* point to a fresh binary search tree node with *m.value* :=  $v$ .

We have three cases:

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We have three cases:

- 1. If  $p = 0$  enull: empty tree, make m the root of the tree.
- 2. If  $v < p$  value: set p.left := m.
- 3. If  $v > p$  value: set p.right := m.

Adding values: Good case We add "just", "is", "a", "it", "or", "not", "word".

> root  $\sqrt{}$

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> $p =$  @null root  $\sqrt{}$

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> root  $\sum_{i=1}^{k}$

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> root p iust






















Adding values: Bad case We add "a", "is", "it", "just", "not", "or", "word".

> root  $\mathbb {V}$

```
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p = @null root
                 \sqrt{}
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> root p  $a^{\frac{1}{k}}$























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We write a *recurrence*  $T(N)$  for the average value of L:

- **►** Either *v* ends up in the left subtree  $\rightarrow$  average length  $T(i) + 1$ .
- 

**►** Or v ends up in the right subtree  $\rightarrow$  average length  $T(N - (i + 1)) + 1$ .

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T(N) = \begin{cases} 0 & \text{if } N = 0; \\ 1 & \text{if } N = 1; \\ \frac{1}{2N} \left( \sum_{i=0}^{N-1} T(i) + 1 + T(N - (i+1)) + 1 \right) & \text{if } N > 1. \end{cases}
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LOG<sub>2</sub>(*i*) = log<sub>2</sub>(*i*), except LOG<sub>2</sub>(0) = 0.

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We have already seen how

- ▶ to traverse a binary search tree;
- $\blacktriangleright$  to search for values in a binary search tree;
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We have not yet seen how to remove values.



Say we want to remove the node  $n$  holding  $v$  from the tree.



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parent of n (or n is root) v  $n -$ 

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Say we want to remove the node  $n$  holding  $\nu$  from the tree. Based on the number of children of n, we have three cases to consider:

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Easy: Just remove node *n* from the parent  $p$ , then remove *n*.



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Consider a binary search tree with N values.

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#### Practical limitation

A lot of data sets are not random: e.g., partially-sorted inputs.