

# **SC1007**

# **Data Structures and**

# **Algorithms**

# **Week 12: Revision**



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# What Is An Algorithm?

- An algorithm is any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as output.

*Introduction to Algorithms*

*-T. H. Cormen et. al.*

# Example : Arithmetic Series

- There are many ways (algorithms) to solve a problem
- Summing up 1 to n

---

## Algorithm 1 Summing Arithmetic Sequence

---

```
1: function Method_One(n)
2: begin
3:   sum  $\leftarrow$  0
4:   for i = 1 to n do
5:     sum  $\leftarrow$  sum + i
6:   end
```

---

---

## Algorithm 2 Summing Arithmetic Sequence

---

```
1: function Method_Two(n)
2: begin
3:   sum  $\leftarrow$  n * (1 + n)/2
4: end
```

---

---

## Algorithm 3 Summing Arithmetic Sequence

---

```
1: function Method_Three(n)
2: begin
3:   if n=1 then
4:     return 1
5:   else
6:     return n+Method_Three(n - 1)
7: end
```

---

# Analysis of Algorithms

- The study of the efficiency and performance of algorithms
- Evaluate the **speed** and **scalability** of an algorithm
  - How its efficiency changes as input sizes grow
- Identify the most efficient algorithms for a given problem
- Understand the trade-offs between different approaches

# Time and space complexities

- Analyze efficiency of an algorithm in two aspects

- Time
- Space



- Time complexity: the amount of time used by an algorithm
- Space complexity: the amount of memory units used by an algorithm



# Time Complexity or Time Efficiency

1. Count the number of **primitive operations** in the algorithm
2. Express it in term of problem size



# Time Complexity or Time Efficiency

## i. Repetition Structure: for-loop, while-loop

```
1: j ← 1 → c0
2: factorial ← 1 → c1
3: while j ≤ n do
4:   factorial ← factorial * j → c2
5:   j ← j + 1 → c3
```

n iterations → n(c<sub>2</sub>+c<sub>3</sub>)

$$f(n) = c_0 + c_1 + n(c_2 + c_3)$$

The function increases linearly with n (problem size)

# Common Complexity Classes

Order of Growth	Class	Example
1	Constant	Finding midpoint of an array
$\log_2 n$	Logarithmic	Binary Search
$n$	Linear	Linear Search
$n \log_2 n$	Linearithmic	Merge Sort
$n^2$	Quadratic	Insertion Sort
$n^3$	Cubic	Matrix Inversion (Gauss-Jordan Elimination)
$2^n$	Exponential	The Tower of Hanoi Problem
$n!$	Factorial	Travelling Salesman Problem

When time complexity of algorithm A grows faster than algorithm B for the same problem, we say A is inferior to B.

# Asymptotic Notations

- Worst-case complexity: Big-Oh (  $O$  )
- Best-case complexity: Big-Omega (  $\Omega$  )
- Average-case complexity: Big-Theta (  $\Theta$  )



# Space Complexity

- Determine number of entities in problem (also called problem size)
- Count number of basic units in algorithm
- Basic units
- Things that can be represented in a constant amount of storage space
- E.g. integer, float and character.



# Space Complexity

- Space requirements for an array of  $n$  integers -  $\Theta(n)$
- If a matrix is used to store edge information of a graph,
  - i.e.  $G[x][y] = 1$  if there exists an edge from  $x$  to  $y$ ,
  - space requirement for a graph with  $n$  vertices is  $\Theta(n^2)$

## Space/time tradeoff principle

- Reduction in time can be achieved by sacrificing space and vice-versa.

# Time Complexity of Sequential Search

```
def search(head, a):
    pt = head
    while pt is not None and pt.key != a:
        pt = pt.next
    return pt
```



Assume that the search key  $a$  is in the list

1. Best-case analysis:  $c_1$  when  $a$  is the first item in the list  $\Rightarrow \Theta(1)$
2. Worst-case analysis:
3. Average-case analysis:

# Time Complexity of Sequential Search

```
def search(head, a):
    pt = head
    while pt is not None and pt.key != a:
        pt = pt.next
    return pt
```

Diagram illustrating the execution flow of the search algorithm:

- Initial state: A sequence of four boxes labeled 1, 2, 3, and 4. Each box has a blue main part and a green suffix.
- Step 1: An arrow points from the first box (labeled  $c_1$ ) to the second box (labeled  $c_1$ ).
- Step 2: An arrow points from the second box (labeled  $c_2$ ) to the third box (labeled  $c_2$ ).
- Step 3: An arrow points from the third box (labeled  $c_2$ ) to the fourth box (labeled  $c_2$ ).
- Step 4: The fourth box (labeled  $c_2$ ) has a diagonal slash through it, indicating it is the target item found.



Assume that the search key  $a$  is in the list

1. Best-case analysis:  $c_1$  when  $a$  is the first item in the list  $\Rightarrow \Theta(1)$
2. Worst-case analysis:  $c_2 \cdot (n-1) + c_1 \Rightarrow \Theta(n)$  when  $a$  is the last item in the list
3. Average-case analysis  
 $p_1 \times \text{time to search for item 1} + p_2 \times \text{time to search for item 2} + \dots + p_n \times \text{time to search for item } n$

# Time Complexity of Sequential Search

```
def search(head, a):
    pt = head
    while pt is not None and pt.key != a:
        pt = pt.next
    return pt
```

$c_1$

$c_2 \quad (n-1) \text{ iterations}$



Assume that the search key  $a$  is always in the list

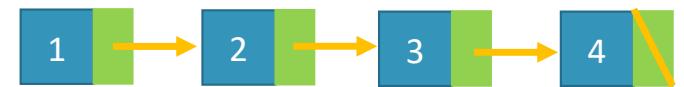
1. Best-case analysis:  $c_1$  when  $a$  is the first item in the list  $\Rightarrow \Theta(1)$
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3. Average-case analysis

# Time Complexity of Sequential Search

```
def search(head, a):
    pt = head
    while pt is not None and pt.key != a:
        pt = pt.next
    return pt
```

$c_1$

$c_2$



If the search key is in the list, on average:

$$c_1 + \frac{c_2(n-1)}{2} = \Theta(n)$$

If the search key,  $a$ , is not in the list, then the time complexity is

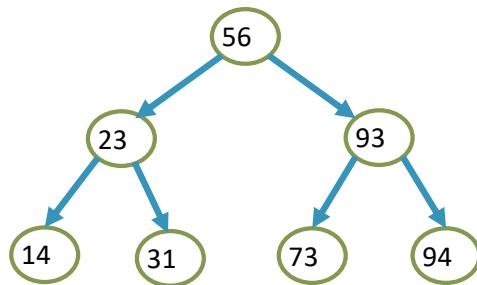
$$c_1 + nc_2 = \Theta(n)$$

# Devide and Conquer: Binary Search

- Given a sorted list



- Whether a search key  $a$  is in the list?
  - Given a sorted list, e.g.,
    - 14, 23, 31, 56, 73, 93, 94
  - We can build a BST

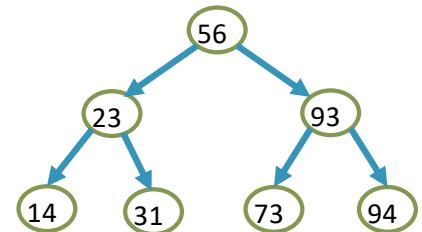


# Time Complexity of Binary Search

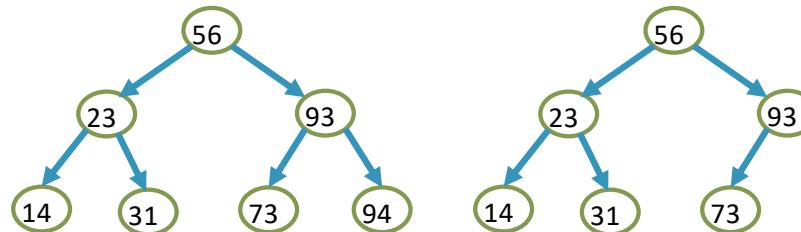
```
def binary_search_recursive(arr, left, right, target):
    if left > right:
        return -1
    mid = left + (right - left) // 2
    if arr[mid] == target:
        return mid
    elif arr[mid] < target:
        return binary_search_recursive(arr, mid + 1, right, target)
    else:
        return binary_search_recursive(arr, left, mid - 1, target)
```

```
def binary_search(self, target, current_node):
    if current_node is None:
        return False
    elif target == current_node.data:
        return True
    elif target < current_node.data:
        return self.binary_search(target, current_node.left)
    else:
        return self.binary_search(target, current_node.right)
```

- Given a sorted list, e.g.,
  - 14, 23, 31, 56, 73, 93, 94
- We can build a BST



# Terminology

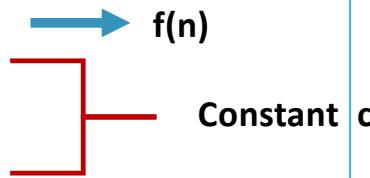


- The Height of a tree: The number of **edges** on the longest path from the root to a leaf
- The Depth of a node: The number of edges from the node to the root of its tree.

$$\text{Height} = \lfloor \log_2 n \rfloor$$

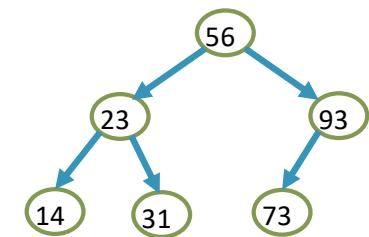
# Binary Search – Worst Case Time Complexity

```
def binary_search(self, target, current_node):  
    if current_node is None:  
        return False  
    elif target == current_node.data:  
        return True  
    elif target < current_node.data:  
        return self.binary_search(target, current_node.left)  
    else:  
        return self.binary_search(target, current_node.right)
```



Constant  $c$

$$f(n) \rightarrow f((n - 1)/2) + f((n - 1)/2)$$



- Assume a complete binary tree

$$\begin{aligned}f(n) &= f\left(\frac{n - 1}{2}\right) + c \\&= \Theta(\log_2 n)\end{aligned}$$

# Binary Search – Average Case Time Complexity

- $A_s(n)$ : # of comparisons for successful search
- $A_f(n)$ : # of comparisons for unsuccessful search (worst case):  $\Theta(\log_2 n)$

$$A(n) = qA_s(n) + (1 - q)A_f(n)$$

$$= \Theta(\log_2 n)$$

# Jump Search

```
def jump_search(arr, target):
    n = len(arr)
    step = int(math.sqrt(n))
    prev = 0

    while prev < n and arr[min(step, n) - 1] < target:
        prev = step
        step += int(math.sqrt(n))
        if prev >= n:
            return -1
    for i in range(prev, min(step, n)):
        if arr[i] == target:
            return i
    return -1
```

- When binary search is costly, e.g., searching for an element in a very large sorted dataset stored on a slow storage medium, like a database on disk or an external hard drive

# Time Complexity of Jump Search

- Assume that the search key  $a$  is in the list
  1. Best-case:  $\Theta(1)$
  2. Worst-case:  $\Theta(\sqrt{n}) + \Theta(\sqrt{n}) = \Theta(\sqrt{n})$
  3. Average-case:  $\sum_{i=1}^{\sqrt{n}} p_i \Theta(\sqrt{n}) = \sum_{i=1}^{\sqrt{n}} \frac{1}{\sqrt{n}} \Theta(\sqrt{n}) = \Theta(\sqrt{n})$
- Assume that the search key  $a$  is not in the list  
 $\Theta(\sqrt{n}) + \Theta(\sqrt{n}) = \Theta(\sqrt{n})$
- On average, the time complexity of Jump Search is  $\Theta(\sqrt{n})$

- Exhaustive Algorithm: Sequential Search
  - Time complexity  $O(n)$
- Decrease-and-conquer Algorithm:
  - Binary Search: Time complexity  $O(\log_2 n)$
  - Jump Search: Time complexity  $O(\sqrt{n})$

	<b>Best Case</b>	<b>Average Case</b>	<b>Worst Case</b>	<b>Overall</b>
Sequential	$\Theta(1)$	$\Theta(n)$	$\Theta(n)$	$O(n)$
Binary	$\Theta(1)$	$\Theta(\log_2 n)$	$\Theta(\log_2 n)$	$O(\log_2 n)$
Jump	$\Theta(1)$	$\Theta(\sqrt{n})$	$\Theta(\sqrt{n})$	$O(\sqrt{n})$

# Hashing

- Hashing: a typical space and time trade-off in algorithm
- To achieve search time in  $O(1)$ , memory usage will be increased

# What is hashing?

- To reduce the key space to a reasonable size
- Each key is mapped to a unique index (**hash value/address**)
- Search time remains  $O(1)$  on the average

**hash function:** {all possible keys}  $\rightarrow \{0, 1, 2, \dots, h-1\}$

- The array is called a **hash table**
- Each entry in the hash table is called a **hash slot**
- When multiple keys are mapped to the same hash value, a **collision** occurs
- If there are  $n$  records stored in a hash table with  $h$  slots, its **load factor** is  $\alpha = \frac{n}{h}$

# Hash Functions

- Must map all possible values within the range of the hash table uniquely
  - Mapping should achieve an even distribution of the keys
  - Easy and fast to compute
  - Minimize collision
- 
1. Modulo Arithmetic
  2. Folding
  3. Mid-square
  4. Etc.

# Hash Functions

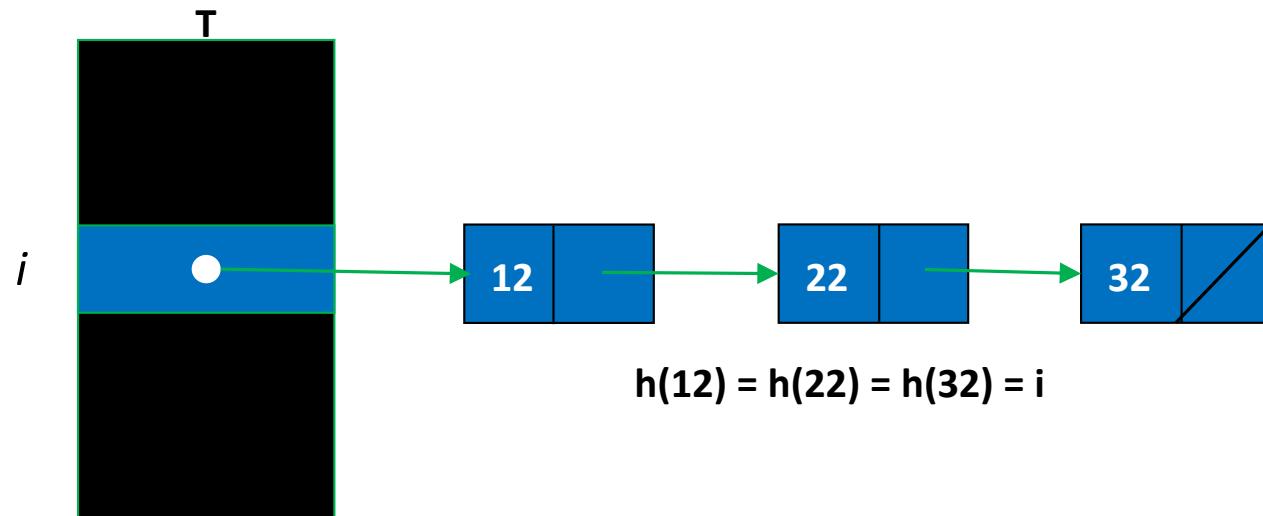
1. Modulo Arithmetic:  $H(k) = k \bmod h$ 
  - E.g.  $h = 13$  &  $k = 37699 \rightarrow H(k) = 37699 \bmod 13 = 12$
  - In practice,  $h$  should be a prime number, but not too close to any power of 2
2. Folding
  - Partition the key into several parts and combine the parts in a convenient way
  - Shift folding: Divide the key into a few parts and added up these parts
  - $X = abc \rightarrow H(X) = (a + b + c) \bmod h$
  - E.g.  $H(123\textcolor{blue}{456}\textcolor{orange}{789}) = (123 + \textcolor{blue}{456} + \textcolor{orange}{789}) \bmod 13 = 3$
3. Mid-square
  - The key is squared and the middle part of the result is used as the hash address
  - E.g.  $k=3121, k^2 = 3121^2 = 97\textcolor{red}{406}41 \rightarrow H(k) = 406$

# Collision Resolutions

- Closed Addressing Hashing – a.k.a separate chaining
- Open Addressing Hashing
  - Linear Probing
  - Quadratic Probing
  - Double Probing

# Closed Addressing: Separate Chaining

- Keys are not stored in the table itself
- All the keys with the same hash address are store in a separate list



- During searching, the searched element with hash address  $i$  is compared with elements in linked list  $H[i]$  sequentially
- In closed address hashing, there will be  $\alpha$  number of elements in each linked list on average  $\alpha = \frac{n}{h}$

# Closed Addressing: Separate Chaining

Time complexity in the **worst-case analysis**:  $\Theta(n)$

Time complexity in the **average-case analysis**:  $\Theta(\alpha)$

# Open Addressing

- Keys are stored in the table itself
- $\alpha$  cannot be greater than 1
- When collision occurs, probe is required for the alternate slot
  - Ideally, the probing approach can visit every possible slot

## 1. Linear Probing: probe the next slot

$$H(k, i) = (k + i) \bmod h \text{ where } i \in [0, h - 1]$$

Primary clustering:

- A long runs of occupied slots
- Average search time is increased

# Open Addressing

## 2. Quadratic Probing

$$H(k, i) = (k + c_1 i + c_2 i^2) \bmod h \quad \text{where } c_1 \text{ and } c_2 \text{ are constants, } c_2 \neq 0$$

- **Secondary Clustering:** if two keys have the same initial probe position, their probe sequences will be the same. This will form a clustering.

# Open Addressing

## 3. Double Hashing: a random probing method

$H(k, i) = (k + iD(k)) \bmod h$       where  $i \in [0, h - 1]$  and  $D(k)$  is another hash function

# Time Complexity

## Linear Probing

- Successful Search:  $\frac{1}{2}(1 + \frac{1}{1-\alpha})$
- Unsuccessful Search:  $\frac{1}{2}(1 + (\frac{1}{1-\alpha})^2)$

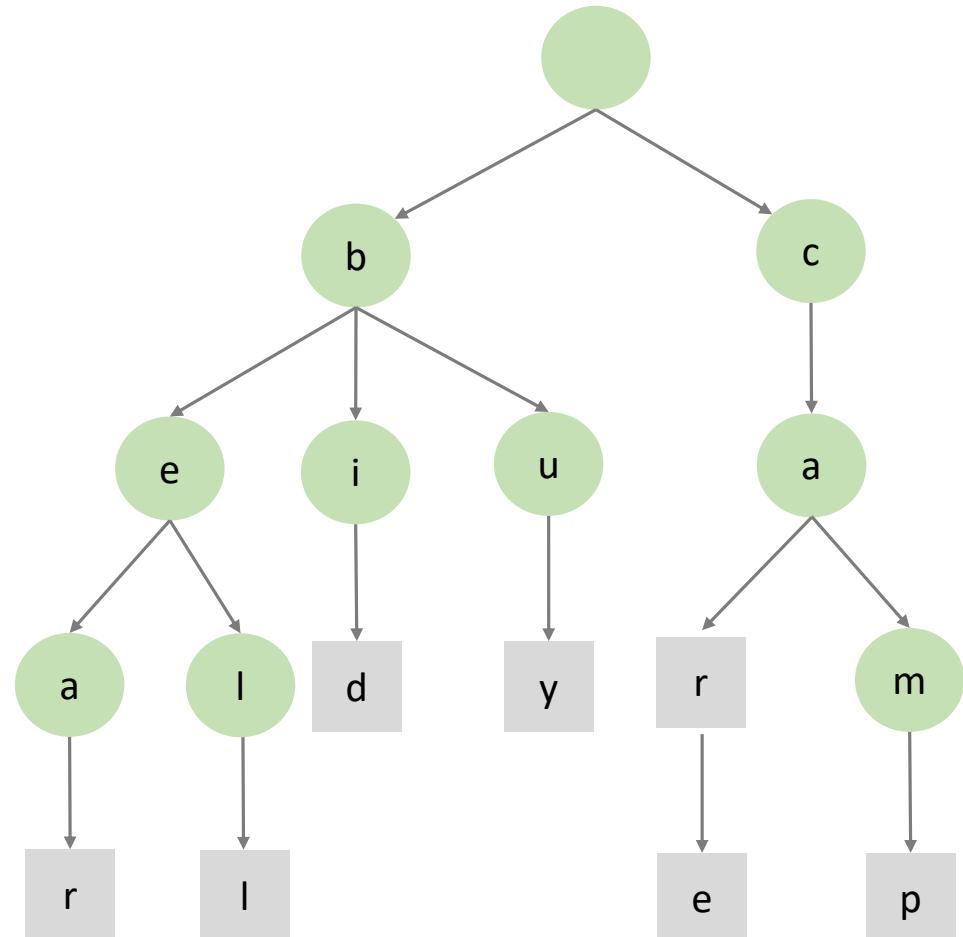
## Double Hashing

- Successful Search:  $\frac{1}{\alpha} \ln \frac{1}{1-\alpha}$
- Unsuccessful Search:  $\frac{1}{1-\alpha}$

\*Proof can be found in The Art of Computer Programming by Knuth Donald (1973)

# What Is a Trie

- A tree-based data structure used for efficient string operations. Also called prefix tree or digital tree.
- It is a specialized search tree data structure used to store and retrieve strings from a dictionary or set.

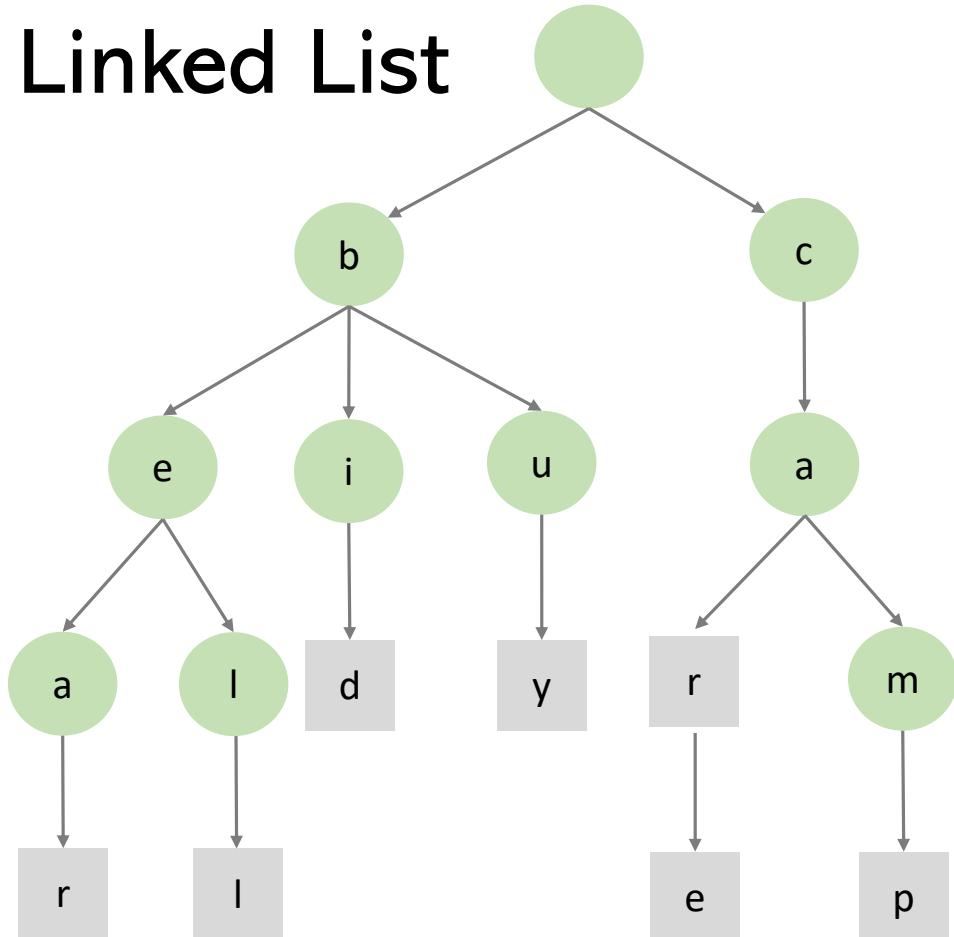


The trie structure for strings: bear, bell, bid, buy, car, care, camp

# Implementations with Linked List

```
class TrieNode:  
    def __init__(self, char):  
        self.char = char  
        self.is_end_of_word = False  
        self.child = None  
        self.next = None
```

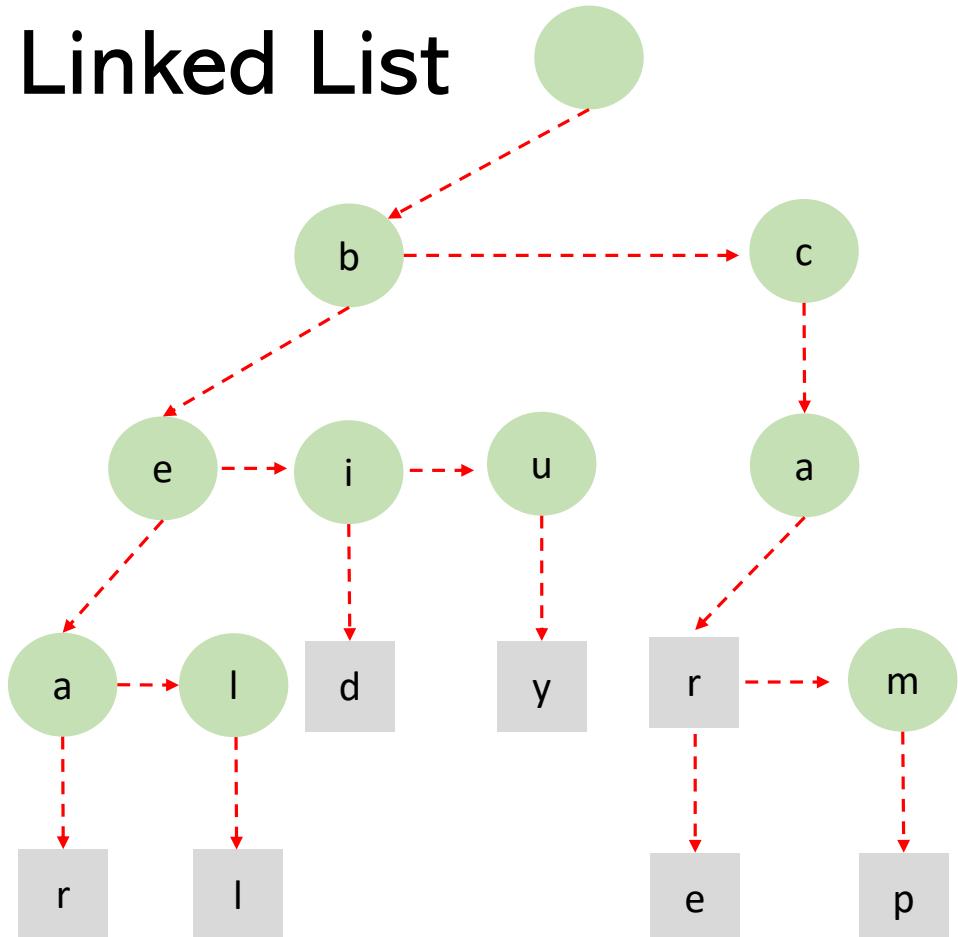
```
char = 'a'  
end_of_word = False  
child = TrieNode('r')  
next = TrieNode('l')
```



# Implementations with Linked List

```
class TrieNode:  
    def __init__(self, char):  
        self.char = char  
        self.is_end_of_word = False  
        self.child = None  
        self.next = None
```

```
char = 'a'  
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```



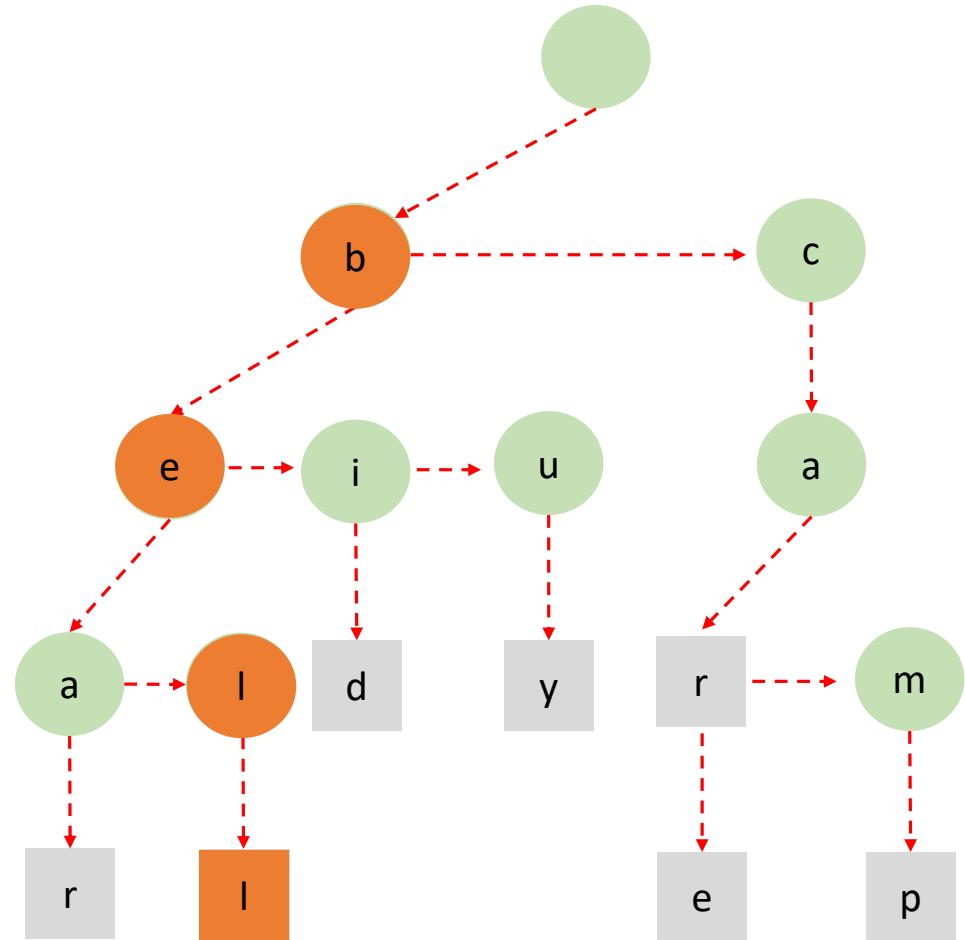
# Implementations with Linked List

- The core operations for a trie:
  - Search a word
  - Insert a word
  - Traversal
- Usually we will not delete a word from a trie
  - Dictionaries don't usually change
  - Deleting from a trie is much more complex than inserting
- The binary tree traversal algorithms can be applied in trie
  - Preorder (dfs)
  - Level-by-level (bfs)

```
class Trie:  
    def __init__(self):  
        self.root = TrieNode("")  
  
    def search(self, word):  
    def insert(self, word):  
    def dfs(self, node):  
    def bfs(self, node):
```

# Search a Word

```
parent_node = root  
for each character in the word  
    if the current character is a  
        child of parent_node:  
            parent_node = current_node  
            move on to the next character  
    else:  
        return False  
return current_node.is_end_of_word
```

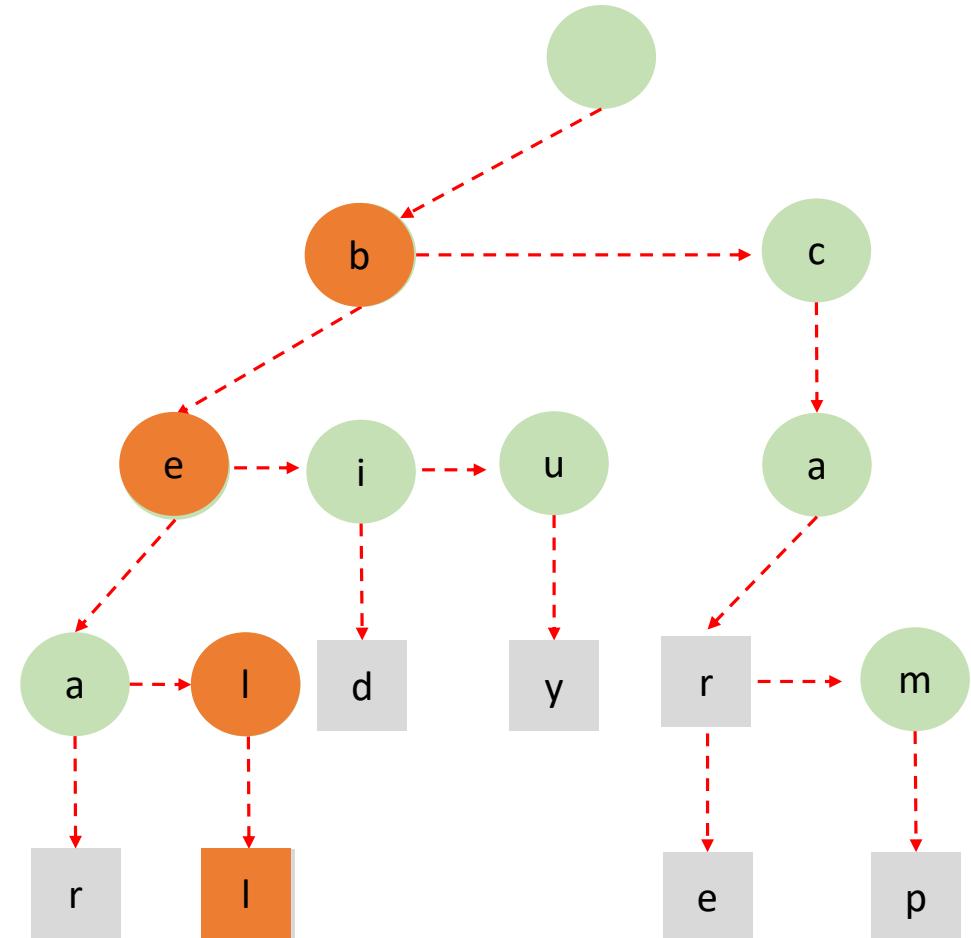


For example, search “bell”

# Search a Word

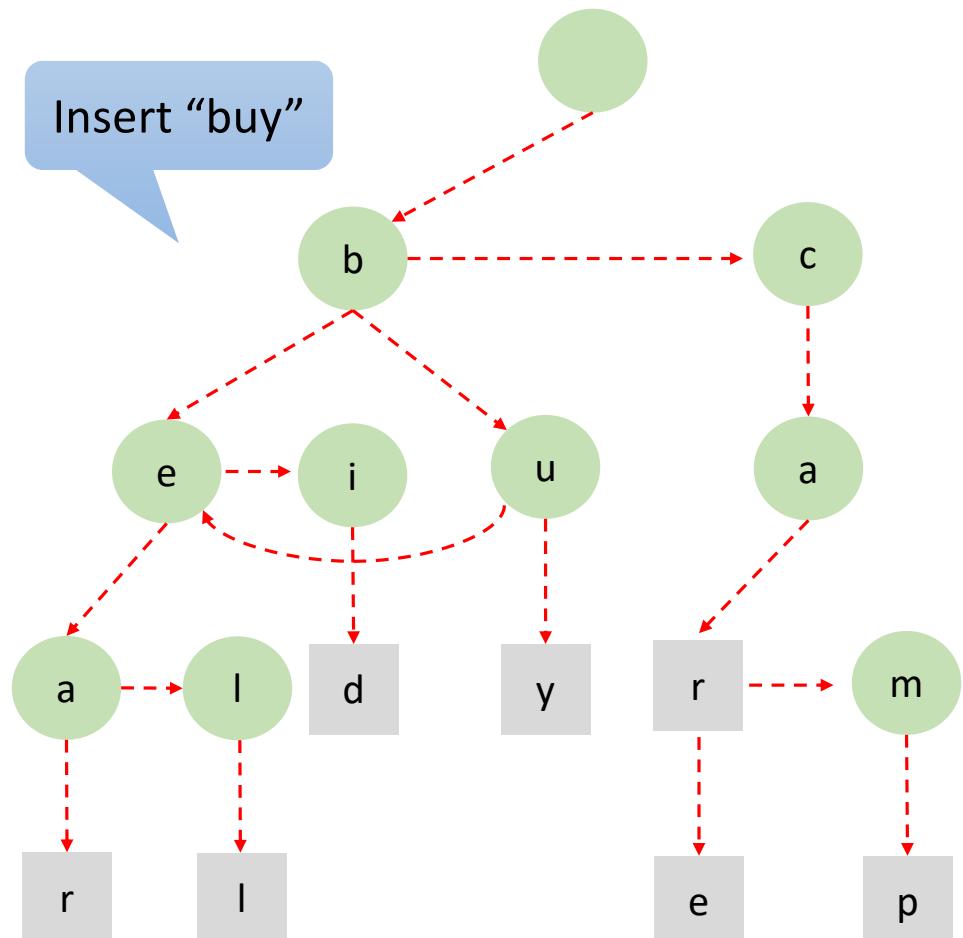
```
def _find_child(self, node, char):
    current = node.child
    while current:
        if current.char == char:
            return current
        current = current.next
    return None

def search(self, word):
    node = self.root
    for char in word:
        node = self._find_child(node, char)
        if not node:
            return False
    return node.is_end_of_word
```



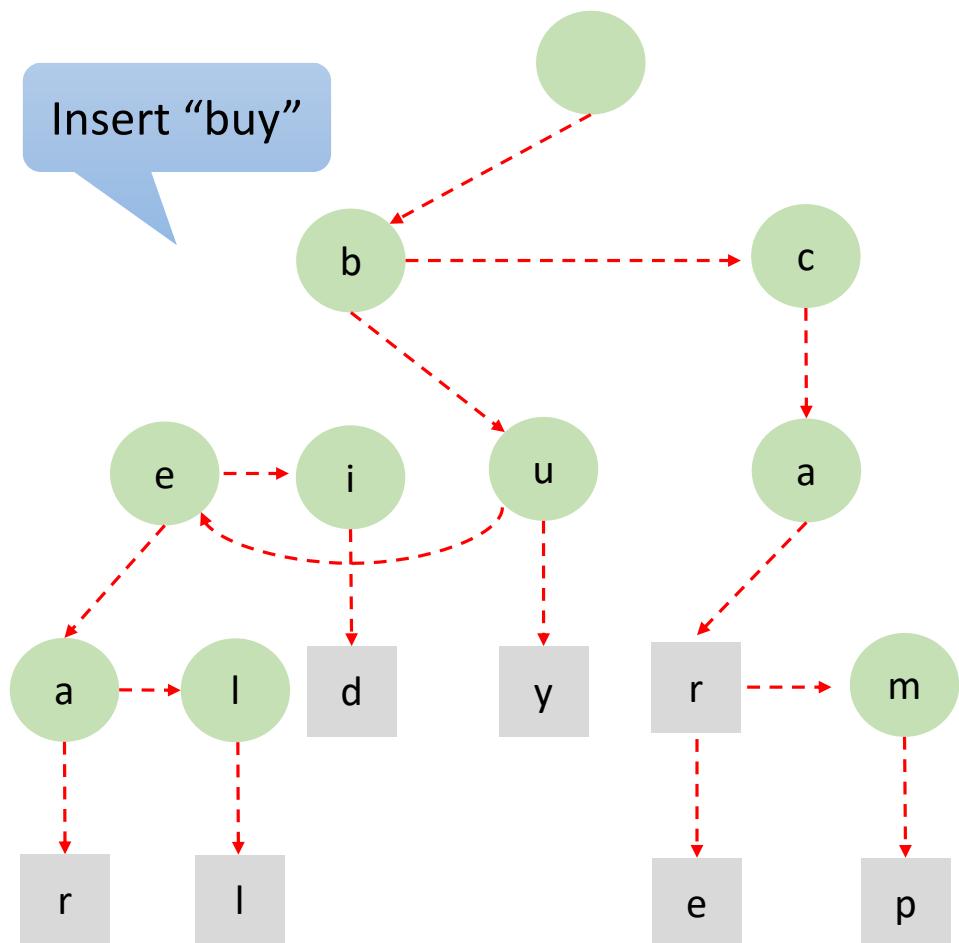
For example, search “bell”

# Insert a Word



```
for each character in the word:  
    if the character is a child node of  
        the parent node:  
            move to the next character  
    else:  
        new_node = create a new TrieNode  
        #insert the child at the beginning  
        #of the linked list  
        set the new_node next be the  
        parent_node's first child  
        set the parent_node first child be  
        the new_node  
  
    set end_of_word of the last_node as True
```

# Insert a word



```
def _add_child(self, node, char):  
    new_node = TrieNode(char)  
    new_node.next = node.child  
    node.child = new_node  
    return new_node  
  
def insert(self, word):  
    node = self.root  
    for char in word:  
        child = self._find_child(node, char)  
        if not child:  
            child = self._add_child(node, char)  
        node = child  
        node.is_end_of_word = True
```

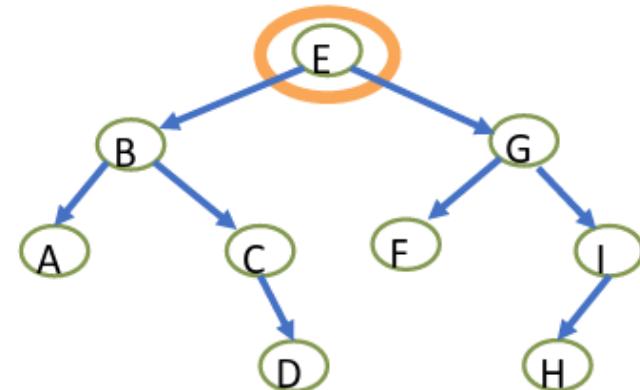


# Pre-order Depth First Traversal

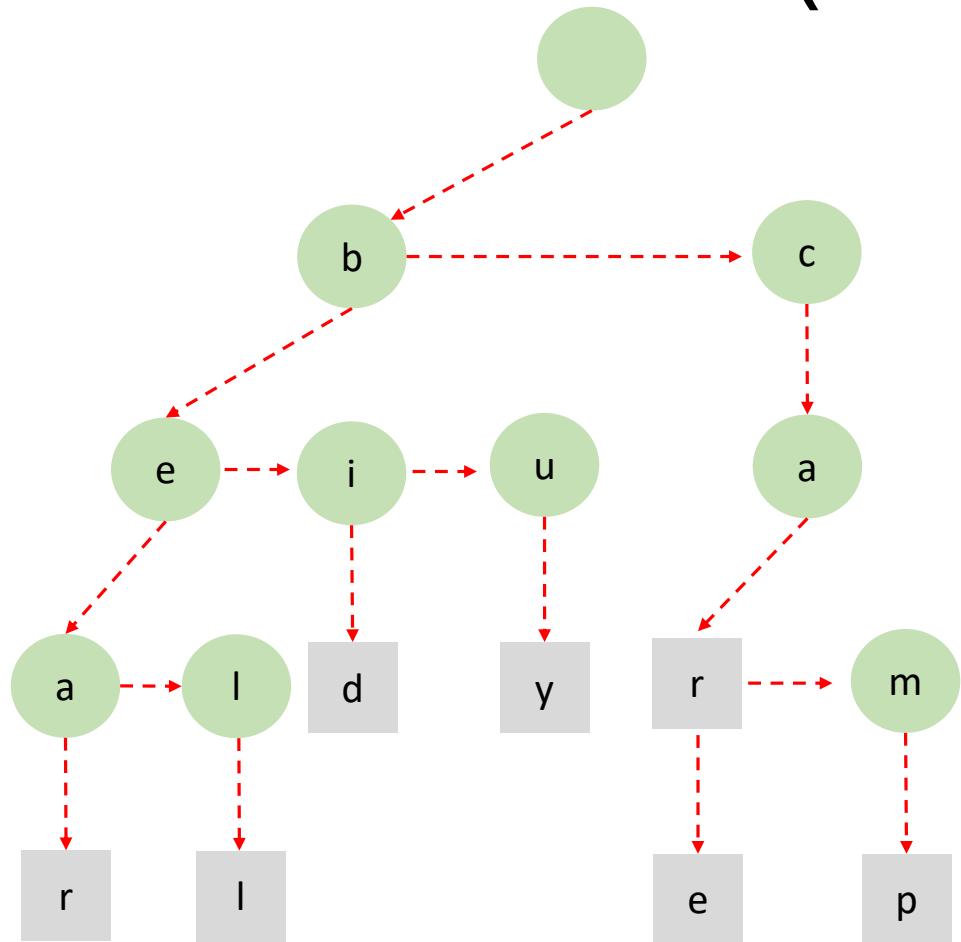
- Pre-order
  - Process the current node's data
  - Visit the left child subtree
  - Visit the right child subtree

TreeTraversal(Node N):

```
Visit N;  
If (N has left child)  
    TreeTraversal(LeftChild);  
If (N has right child)  
    TreeTraversal(RightChild);  
Return; // return to parent
```



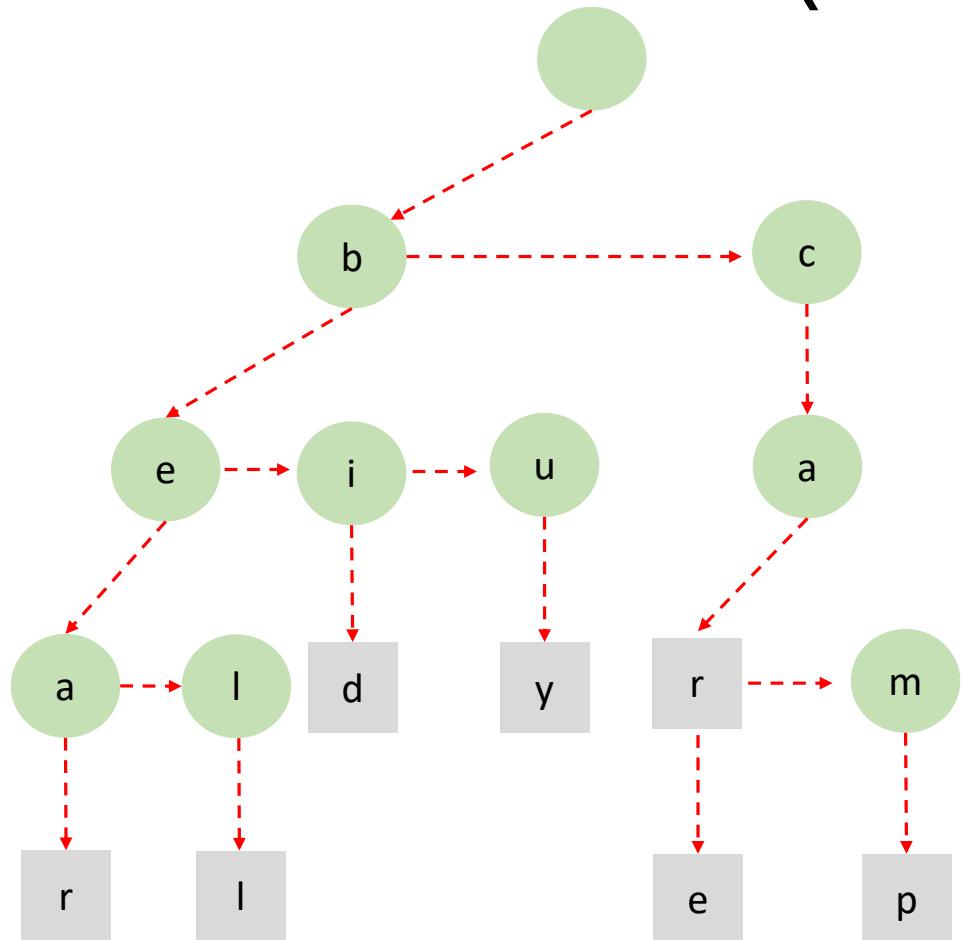
# Preorder Traversal (DFS)



Instead of visiting left and right children,  
visit each child of the TrieNode

```
dfs(TrieNode tn) :  
    visit tn  
    child = tn.child  
    while child is not None:  
        dfs(child)  
        child = child.next
```

# Preorder Traversal (DFS)



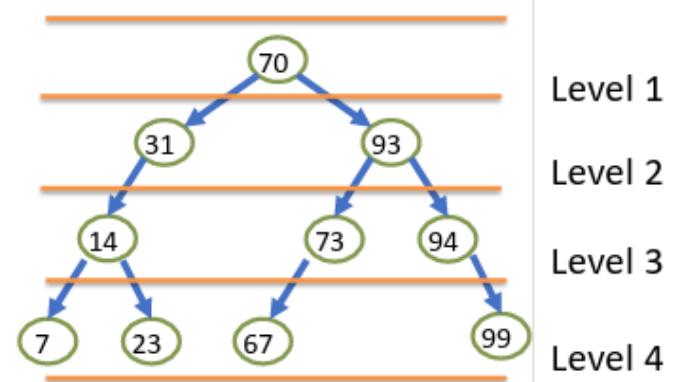
```
def dfs(self, node):  
    if node is not None:  
        print(node.char, end=" ")  
        child = node.child  
        while child:  
            self.dfs(child)  
            child = child.next
```

None bear!!! duycaremp

# Breath-first Traversal: Level-by-level

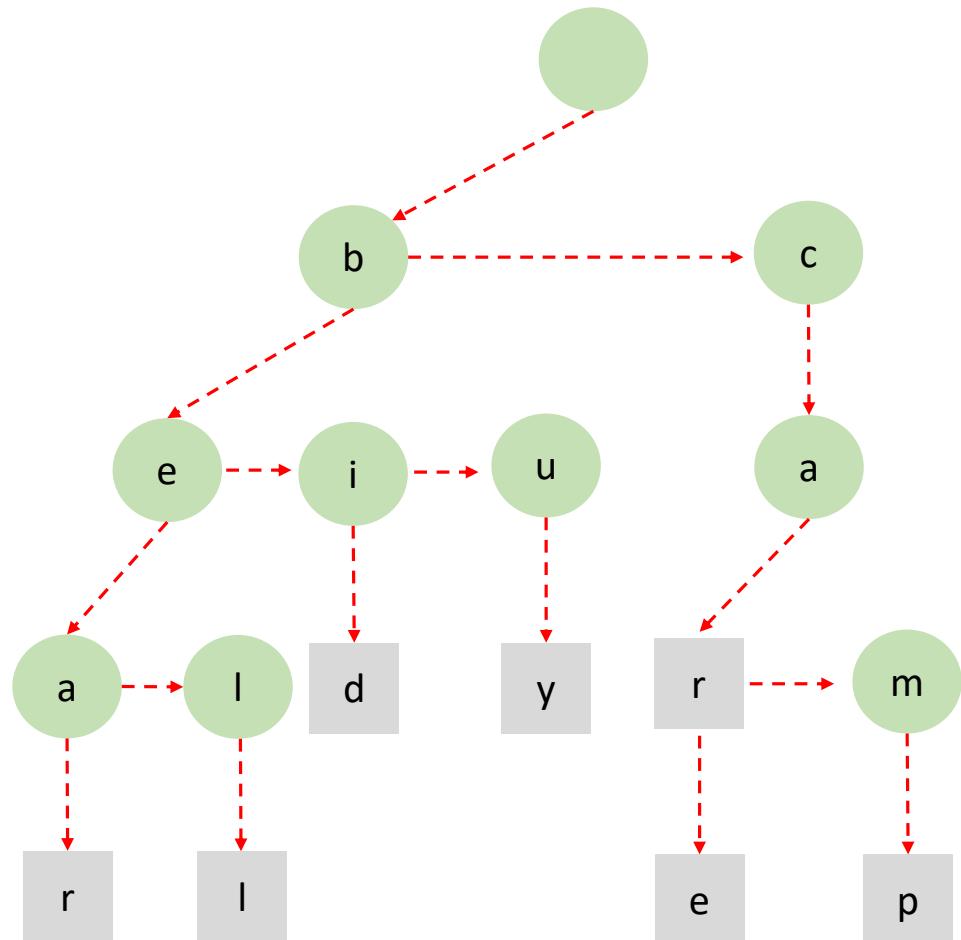
Level-By-Level Traversal:

- Visiting a node
- Remember all its children
  - Use a queue (FIFO structure)



1. Enqueue the current node
2. Dequeue a node
3. Enqueue its children if it is available
4. Repeat Step 2 until the queue is empty

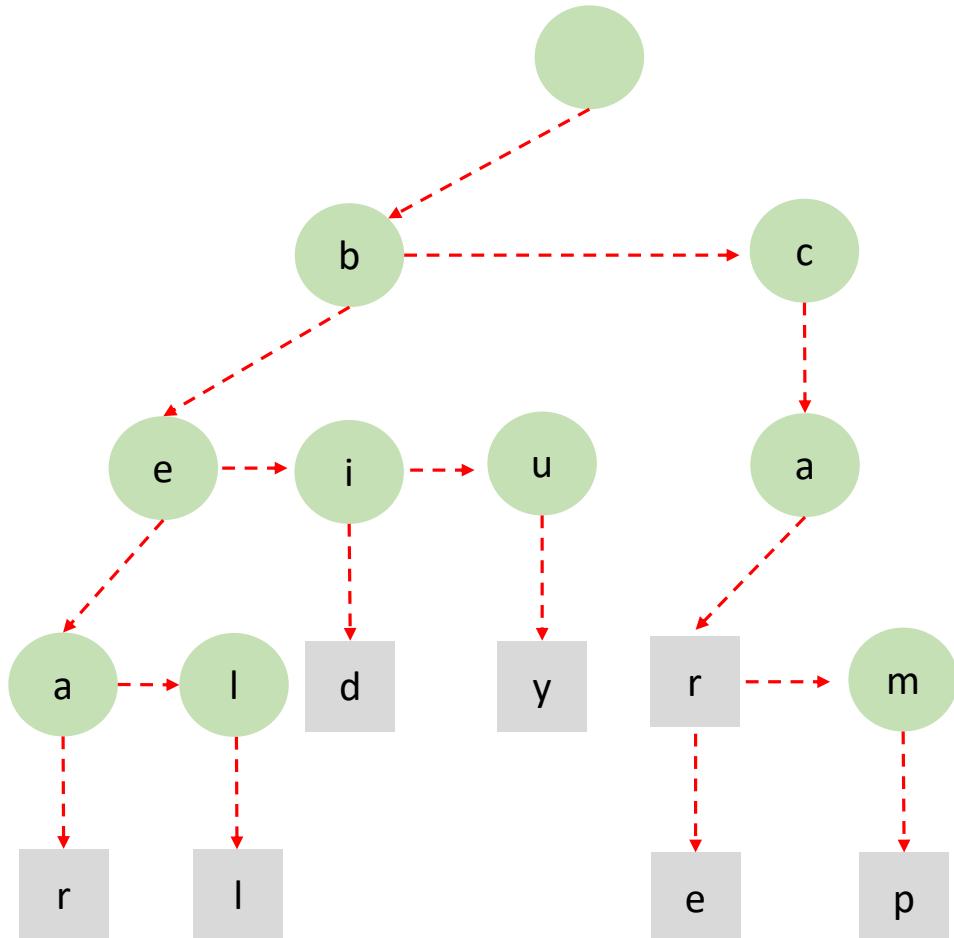
# Level-by-Level Traversal (BFS)



```
def bfs(self):  
    queue = Queue()  
    queue.enqueue(self.root)  
    while not queue.is_empty():  
        node = queue.dequeue()  
        print(node.char, end=" ")  
        child = node.child  
        while child:  
            queue.enqueue(child)  
            child = child.next
```

None b c e i u a a l d y r m r l e p

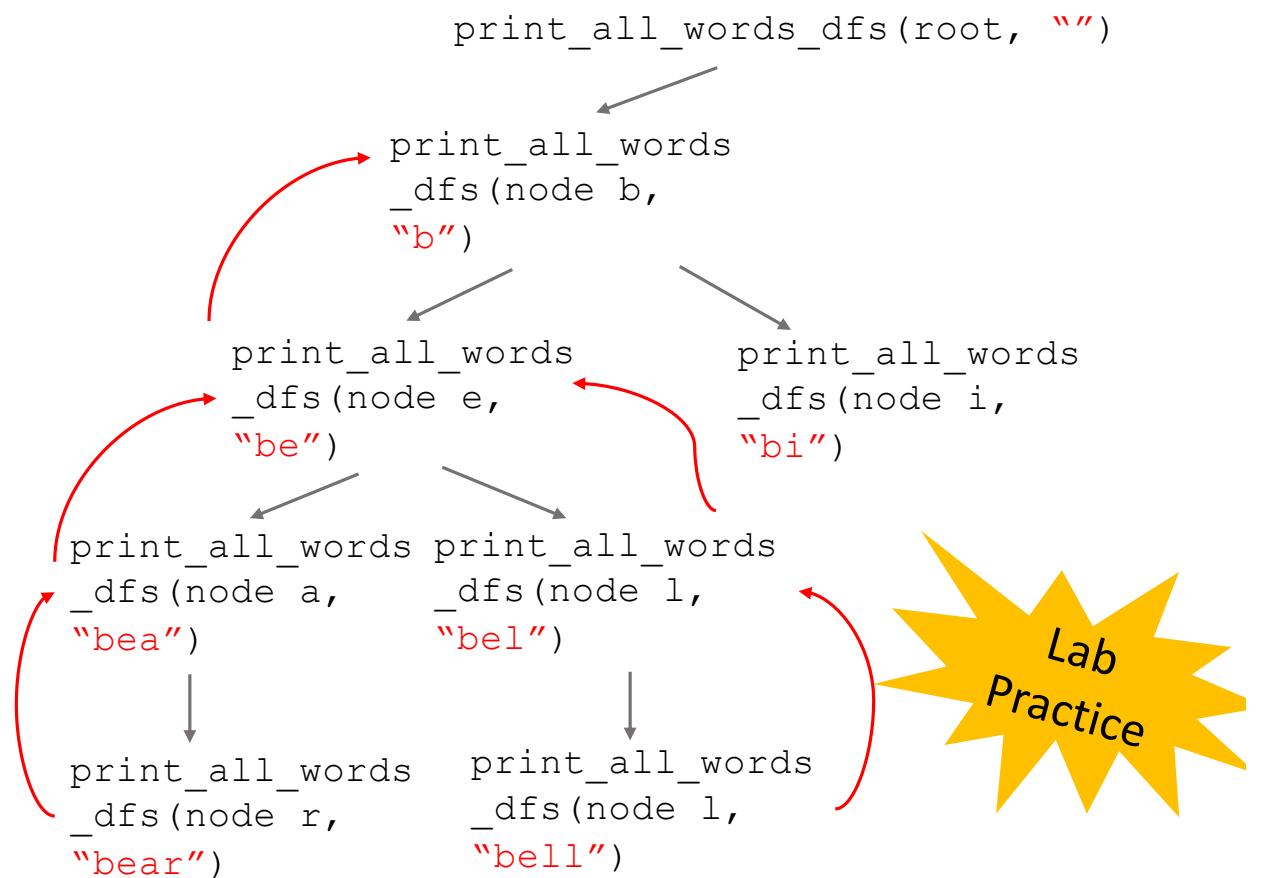
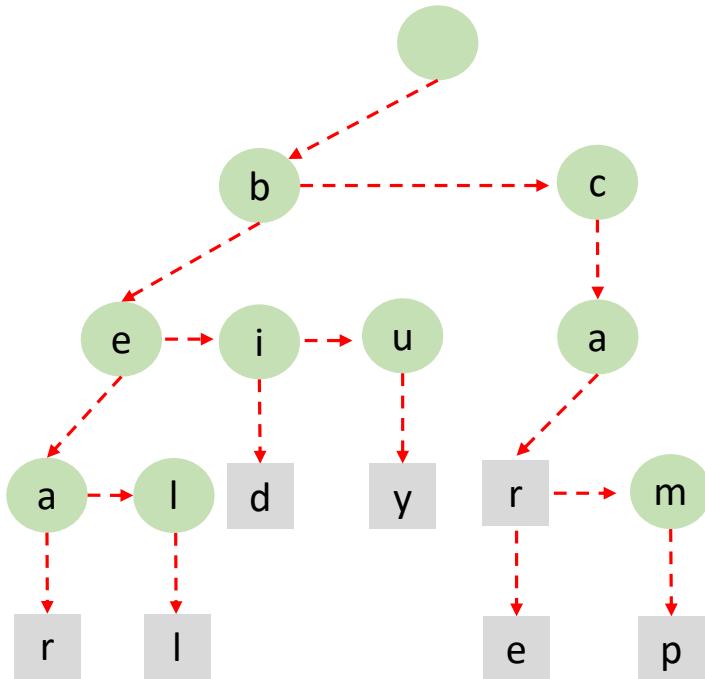
# Working Example: Print All Words



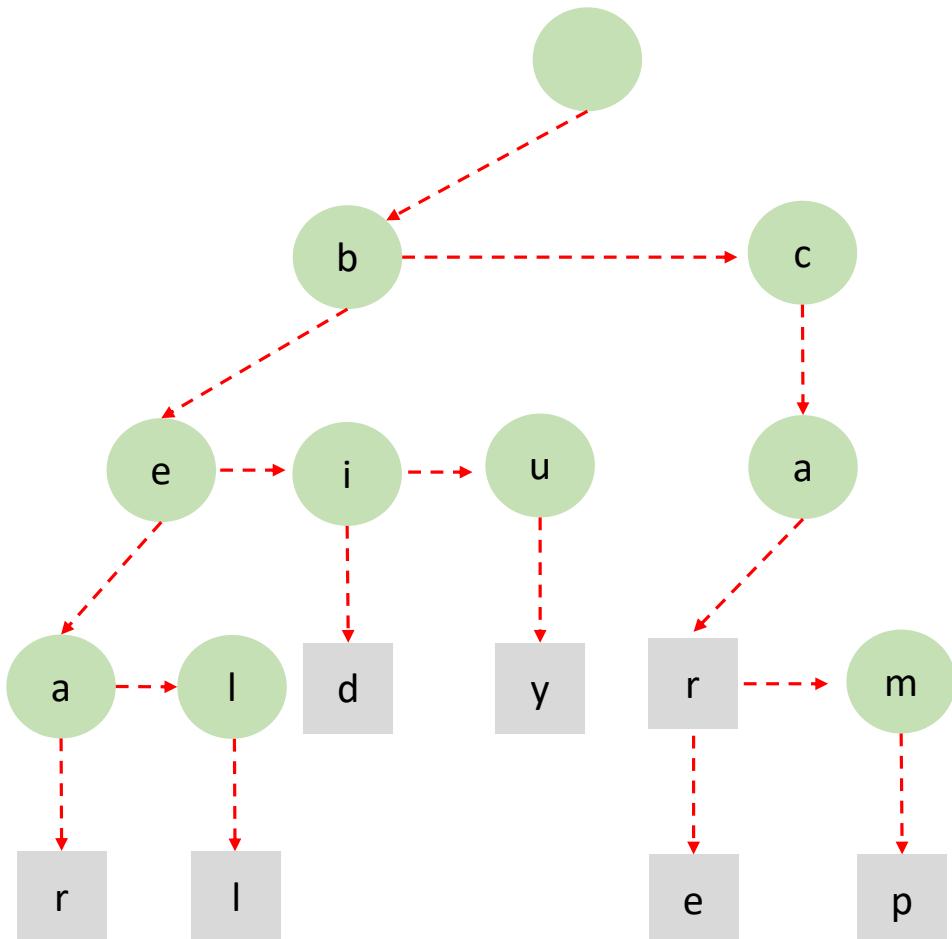
- Apply dfs
- When the node is the end of a word, print it
- Keep track of current nodes' ancestors

```
def print_all_words_dfs(self, node, prefix):  
    if node.is_end_of_word:  
        print(prefix)  
  
    child = node.child  
    while child:  
        self.print_all_words(child,  
                             prefix+child.char)  
        child = child.next
```

# Working Example: Print All Words



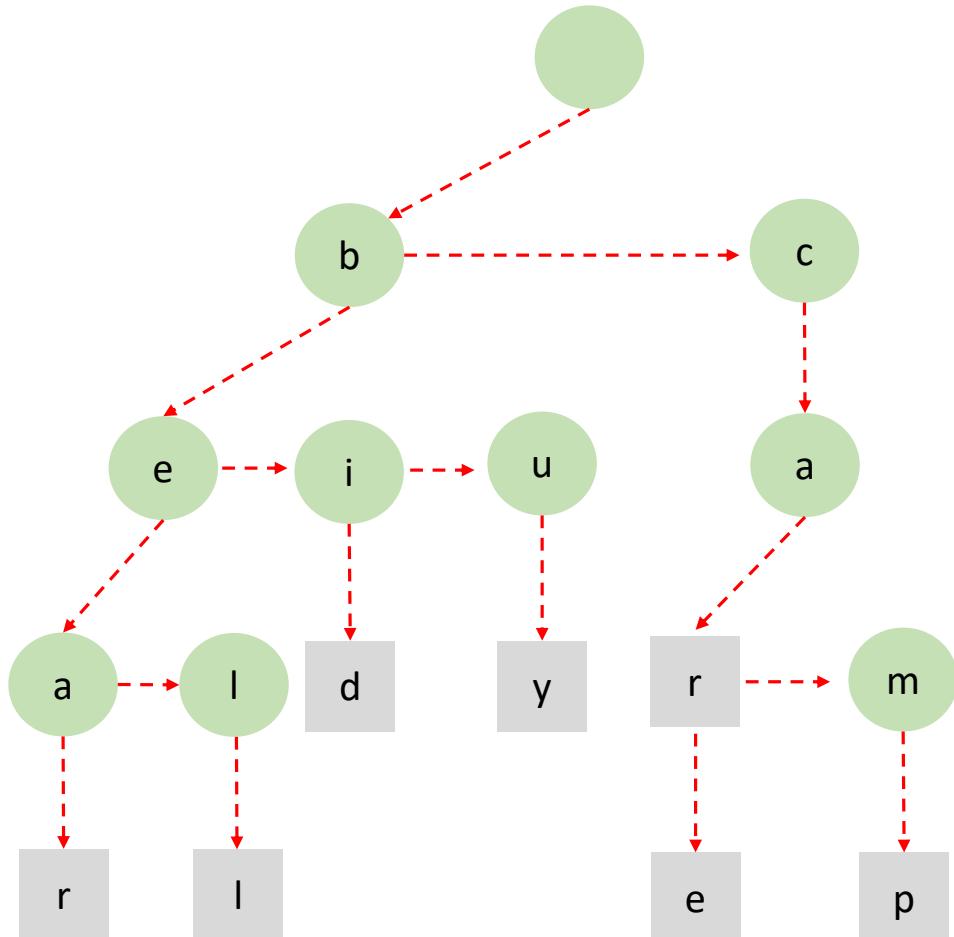
# Working Example: Print All Words



- Apply bfs
- When enqueue a node, also enqueue the node's ancestors & the node's character
- When dequeue a node, if the node is end of a word, print the word

```
class Queue:  
    def __init__(self):  
        self.items = []  
    def enqueue(self, item):  
        self.items.append(item)  
    def dequeue(self):  
        if not self.is_empty():  
            return self.items.pop(0)  
        return None  
    def is_empty(self):  
        return len(self.items) == 0
```

# Working Example: Print All Words



```
def print_all_words_bfs(self):  
    queue = Queue()  
    queue.enqueue((self.root, ""))  
    while not queue.is_empty():  
        node, prefix = queue.dequeue()  
        if node.is_end_of_word:  
            print(prefix)  
        child = node.child  
        while child:  
            queue.enqueue((child,  
                           prefix + child.char))  
            child = child.next
```

Tutorial Practice