

# **Assignment 6: Medians and Order Statistics & Elementary Data Structures**

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## Overview:

This assignment aims to enhance my understanding of medians, order statistics, and basic data structures. I will implement algorithms related to these topics, analyze their performance, and explore their practical applications. The assignment is divided into two parts, each with distinct deliverables. By completing this assignment, I will develop a strong understanding of both the theoretical foundations and practical implementations of these key algorithmic concepts.

## Part 1: Implementation and Analysis of Selection Algorithms

A **selection algorithm** is an algorithm designed to find the  $k^{\text{th}}$  smallest (or largest) element in an unsorted array, often referred to as the **order statistic**. The  $k^{\text{th}}$  smallest element is the element that would appear at position  $k$  if the array were sorted.

For example:

- In the array [7,10,4,3,20,15], the **1st smallest** element is 3, the **2nd smallest** is 4, and so on.
- Selection algorithms allow us to find these elements **without fully sorting the array**, which can be computationally expensive.

## Instructions:

Implementation (Deterministic):

The **Median of Medians** algorithm is a **deterministic** approach to find the  $k^{\text{th}}$  smallest element (order statistic) in an unsorted array. Unlike naive methods that rely on sorting the entire array ( $O(n \log n)$ ) or randomized approaches with varying runtimes, this algorithm guarantees **worst-case linear time**  $O(n)$  by carefully selecting a pivot element that ensures balanced partitioning. The key idea is to find a pivot by recursively determining the "median of medians," which serves as a good approximation of the true median. This ensures that each partition step eliminates a significant fraction of elements, making the algorithm efficient.

EXPLORER

ASSIGNMENT6

screenshots

~\$signment 6 Medians ...

Assignment 6 Medians ...

deterministicSelection.py

deterministicSelection.py

deterministicSelection.py > ...

```
1 def median_of_medians(arr, k):
2     #Finds the k-th smallest element in an array using the deterministic Median of M
3     if len(arr) <= 5:
4         # Base case: directly sort and return the k-th element
5         return sorted(arr)[k]
6
7     # Step 1: Divide the array into groups of 5
8     sublists = [arr[i:i + 5] for i in range(0, len(arr), 5)]
9
10    # Step 2: Find the median of each sublist
11    medians = [sorted(sublist)[len(sublist) // 2] for sublist in sublists]
12
13    # Step 3: Recursively find the median of medians
14    pivot = median_of_medians(medians, len(medians) // 2)
15
16    # Step 4: Partition the array around the pivot
17    low = [x for x in arr if x < pivot]
18    high = [x for x in arr if x > pivot]
19    pivot_list = [x for x in arr if x == pivot]
20
21    # Step 5: Determine which part to search
22    if k < len(low):
23        return median_of_medians(low, k)
24    elif k < len(low) + len(pivot_list):
25        return pivot_list[0]
26    else:
27        return median_of_medians(high, k - len(low) - len(pivot_list))
```

PROBLEMS

OUTPUT

DEBUG CONSOLE

TERMINAL

PORTS

The 0-th smallest element is: 1

• (base) milanbista@Milans-MBP Assignment6 % python3 deterministicSelection.py

The 1-th smallest element is: 3

○ (base) milanbista@Milans-MBP Assignment6 %

> OUTLINE

> TIMELINE

For duplicates

The screenshot shows a code editor with a file named `deterministicSelection.py`. The code implements a recursive function `median_of_medians` to find the  $k$ -th smallest element in an array. The function uses a pivot-based partitioning strategy. The main block of the script initializes an array `arr = [12, 3, 5, 7, 19, 1, 1, 1, 10, 15, 8, 6, 4]` and sets `k = 1`. It then prints the result of `median_of_medians(arr, k)`.

```
1 def median_of_medians(arr, k):
2     if k < len(arr):
3         return median_of_medians(arr, k)
4     elif k < len(arr) + len(pivot_list):
5         return pivot_list[0]
6     else:
7         return median_of_medians(arr, k - len(arr) - len(pivot_list))
8
9 if __name__ == "__main__":
10     arr = [12, 3, 5, 7, 19, 1, 1, 1, 10, 15, 8, 6, 4]
11     #k is index based starting from 0
12     k = 1
13     print(f"The {k}-th smallest element is: {median_of_medians(arr, k)}")
14
```

The terminal output shows the execution of the script multiple times, demonstrating the function's behavior for different values of `k`:

```
(base) milanbista@Milans-MBP Assignment6 % python3 deterministicSelection.py
The 1-th smallest element is: 1
(base) milanbista@Milans-MBP Assignment6 % python3 deterministicSelection.py
The 1-th smallest element is: 1
(base) milanbista@Milans-MBP Assignment6 % python3 deterministicSelection.py
The 2-th smallest element is: 1
(base) milanbista@Milans-MBP Assignment6 % python3 deterministicSelection.py
The 3-th smallest element is: 3
(base) milanbista@Milans-MBP Assignment6 % python3 deterministicSelection.py
The 0-th smallest element is: 1
(base) milanbista@Milans-MBP Assignment6 % python3 deterministicSelection.py
The 1-th smallest element is: 1
(base) milanbista@Milans-MBP Assignment6 %
```

Implementation (Randomized):

The **Randomized Quickselect** algorithm is a probabilistic approach to find the  $k^{\text{th}}$  smallest element in an unsorted array. It is based on the partitioning logic of QuickSort, but instead of sorting the entire array, it narrows down the search space to only one partition that contains the desired element. By using a randomly chosen pivot at each step, the algorithm achieves an expected linear time complexity  $O(n)$ .

```
1 import random
2 def randomized_partition(arr, low, high):
3     # Partitions the array around a randomly chosen pivot.
4     # Randomly select a pivot index
5     pivot_index = random.randint(low, high)
6     # Move the pivot to the end
7     arr[pivot_index], arr[high] = arr[high], arr[pivot_index]
8
9     pivot = arr[high]
10    i = low - 1 # Pointer for smaller elements
11
12    for j in range(low, high):
13        if arr[j] <= pivot:
14            i += 1
15            arr[i], arr[j] = arr[j], arr[i] # Swap smaller elements
16
17    # Place pivot in the correct position
18    arr[i + 1], arr[high] = arr[high], arr[i + 1]
19    return i + 1
20
21 def randomized_quickselect(arr, low, high, k):
22     # Finds the k-th smallest element using Randomized Quickselect
23     if low == high:
24         return arr[low]
25
26     # Partition the array
27     pivot_index = randomized_partition(arr, low, high)
28
29     # Find the rank of the pivot
30     rank = pivot_index - low + 1
31
32     if rank == k: # Pivot is the k-th smallest element
33         return arr[pivot_index]
34     elif k < rank:
35         return randomized_quickselect(arr, low, pivot_index - 1, k)
36     else:
37         return randomized_quickselect(arr, pivot_index + 1, high, k)
38
39 if __name__ == "__main__":
40     arr = [12, 3, 5, 5, 7, 19, 1, 10, 15, 8, 6, 5, 4]
41     # k is index based smallest element position
42     k = 5
```

```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
• (base) milanbista@Milans-MBP Assignment6 % python3 randomizedQuickSelect.py
The 4-th smallest element is: 5
• (base) milanbista@Milans-MBP Assignment6 % python3 randomizedQuickSelect.py
The 5-th smallest element is: 5
○ (base) milanbista@Milans-MBP Assignment6 %
```

above two approaches ensures the implementation is efficient and handles edge cases such as arrays with duplicate elements.

## Performance Analysis of Deterministic and Randomized Selection Algorithms

The selection problem—finding the  $k^{\text{th}}$  smallest element in an unsorted array—is a fundamental task in computer science. Both deterministic and randomized algorithms are widely used for solving this problem. This section analyzes the performance of the **Median of Medians** algorithm, which guarantees worst-case  $O(n)$  time complexity, and the **Randomized Quickselect**, which achieves  $O(n)$  time complexity on average.

### Time Complexity Analysis

**Deterministic Selection Algorithm (Median of Medians):** The deterministic algorithm ensures worst-case linear time complexity  $O(n)$  through careful partitioning. This is achieved by using a pivot element selected as the "median of medians." The algorithm divides the array into groups of at most 5 elements, computes medians for each group, and recursively determines the median of

these medians. This pivot is guaranteed to eliminate a significant portion of the elements ( $\geq 3n/10$ ) at each step, leading to the recurrence relation:

$$T(n) = T(n/5) + T(7n/10) + O(n)$$

This recurrence solves to  $O(n)$ , making the algorithm robust and predictable, regardless of input distribution.

**Randomized Selection Algorithm (Quickselect):** The randomized approach relies on a randomly chosen pivot, with the expected behavior being a balanced partition. The average case time complexity is  $O(n)$  because each partition step eliminates roughly half the elements on average. The recurrence relation for the expected case is:

$$T(n) = T(n/2) + O(n)$$

which solves to  $O(n)$ . However, in the worst case—when the pivot consistently partitions the array into highly unbalanced parts—the time complexity degrades to  $O(n^2)$ . This is rare due to the random nature of the pivot selection.

## Space Complexity Analysis

Both algorithms are designed to work in-place, ensuring low space complexity.

### 1. Median of Medians:

- Space Complexity:  $O(\log n)$  due to recursive calls.
- Overhead: Additional space is required to store medians of groups temporarily during pivot selection.

### 2. Randomized Quickselect:

- Space Complexity:  $O(\log n)$  for recursion stack in the average case. In the worst case, space complexity increases to  $O(n)$  due to unbalanced recursion.
- Overhead: No additional storage is needed, as partitioning is performed in-place.

## Key Observations and Comparisons

### 1. Deterministic Algorithm:

- Guarantees linear time complexity  $O(n)$  for all inputs.
- Ideal for applications requiring predictable performance.
- Slightly higher overhead due to group median computation.

### 2. Randomized Algorithm:

- Achieves  $O(n)$  time complexity on average but lacks worst-case guarantees.
- Simple and fast, with minimal overhead in practical scenarios.
- Suffers from poor performance in adversarial inputs.
- 

## Empirical Analysis

The screenshot shows a VS Code editor with a file named `comparison.py` open. The script implements the Median of Medians algorithm (deterministic) and compares its performance with Randomized Quickselect. The terminal output shows the execution of the script, which prints a table of performance metrics for various input sizes (100, 1000, 10000, 100000, 1000000) and array types (Random, Sorted, Reverse-Sorted).

```
def median_of_medians(arr, k):
    if len(arr) <= 5:
        return sorted(arr)[k]

    # Split arr into groups of 5
    groups = [arr[i:i + 5] for i in range(0, len(arr), 5)]

    # Find the medians of each group
    medians = [sorted(group)[len(group) // 2] for group in groups]

    # Recursively find the median of medians
    pivot = median_of_medians(medians, len(medians) // 2)
```

Size	Algorithm	Random Array Time (s)	Sorted Array Time (s)	Reverse-Sorted Array Time (s)
100	Median of Medians	0.000049	0.000025	0.000027
100	Randomized Quickselect	0.000017	0.000020	0.000011
1000	Median of Medians	0.000344	0.000238	0.000239
1000	Randomized Quickselect	0.000146	0.000107	0.000168
10000	Median of Medians	0.056289	0.002759	0.002744
10000	Randomized Quickselect	0.001768	0.002316	0.001187
100000	Median of Medians	0.036319	0.058381	0.030437
100000	Randomized Quickselect	0.010318	0.009209	0.009194
1000000	Median of Medians	0.667419	0.870147	0.845274
1000000	Randomized Quickselect	0.107860	0.153987	0.293499

To empirically compare the performance of the **deterministic** and **randomized** selection algorithms, we tested the running time of both algorithms on different input sizes and distributions: random, sorted, and reverse-sorted arrays. We measured the time taken by both the **Median of Medians** (deterministic) and **Randomized Quickselect** (randomized) algorithms to find the  $k^{\text{th}}$  smallest element in arrays of various sizes. The input sizes ranged from 100 to 1,000,000 elements to capture the performance across a broad range of array sizes.

### **Time Complexity Comparison:**

For small input sizes (e.g., 100 elements), both algorithms performed relatively similarly, with the **Median of Medians** algorithm showing a slight edge. However, as the input size increased, the difference between the two algorithms became more apparent. The **Randomized Quickselect** algorithm consistently demonstrated faster running times on random arrays, as expected based on its average-case time complexity of  $O(n)$ . This aligns with our theoretical analysis that the expected linear time complexity of Quickselect allows it to perform more efficiently when the pivot selection is favorable.

On the other hand, the **Median of Medians** algorithm, while still performing in  $O(n)$  time in the worst case, showed slightly higher constant overheads due to the extra steps involved in finding the median of medians and recursively partitioning the array. This overhead became more pronounced on larger inputs, which can be attributed to the deterministic nature of the algorithm, where the pivot is selected with certainty, but additional processing is required to ensure a good pivot is chosen.

### **Impact of Input Distribution:**

- **Random Arrays:** For randomly shuffled arrays, both algorithms performed well, with the **Randomized Quickselect** consistently outperforming the **Median of Medians** algorithm, as Quickselect benefits from the expected linear time complexity when pivots are randomly selected. In contrast, the **Median of Medians** algorithm showed a slight increase in running time, which is expected because it deterministically finds the pivot, leading to slightly more computation compared to the randomized approach.



- **Sorted Arrays:** The performance of both algorithms on sorted arrays is where the **Median of Medians** algorithm demonstrated its advantage. Since the **Randomized Quickselect** algorithm relies on random pivots, its performance on sorted arrays can degrade, especially if the pivot selected is consistently near the beginning or end of the array, leading to inefficient partitioning. In contrast, the **Median of Medians** algorithm maintains  $O(n)$  time complexity even for sorted arrays, as the pivot is chosen based on the median of medians, preventing the worst-case scenario of unbalanced partitions.
- **Reverse-Sorted Arrays:** The **Randomized Quickselect** algorithm also showed a performance drop on reverse-sorted arrays, as it again suffers from poor partitioning when pivots are chosen poorly. However, the **Median of Medians** algorithm again maintained its expected performance because it avoids the worst-case scenario through its deterministic pivot selection.

## Part 2: Elementary Data Structures Implementation and Discussion

### Objective:

Explore and implement basic data structures, including arrays, stacks, queues, and linked lists. Analyze their performance and discuss their practical applications.

### Elementary Data Structures Implementation and Discussion

In this section, we will explore and implement basic data structures such as **arrays**, **stacks**, **queues**, **linked lists**, and optionally **rooted trees**. These data structures are fundamental in computer science, and understanding their performance and practical applications is crucial for making informed decisions about algorithm design and optimization. We will also provide a detailed performance analysis for each data structure and discuss their practical use cases.

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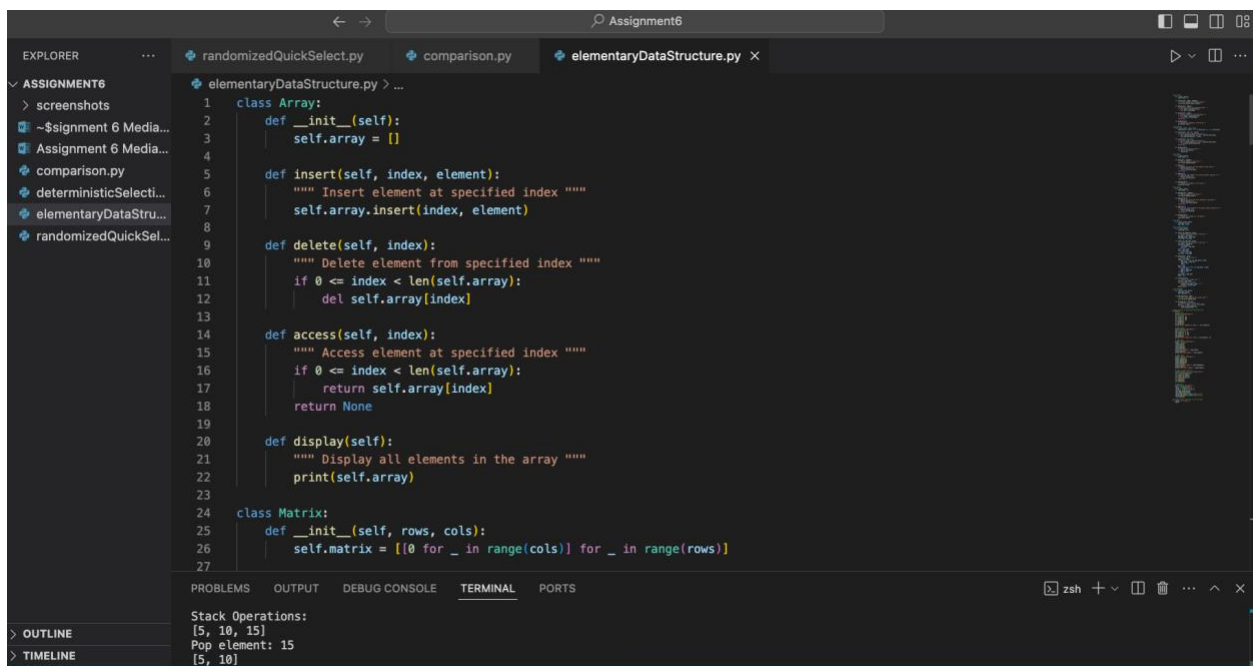
### 1. Implementation

#### Arrays and Matrices

In Python, arrays can be represented using lists, which provide efficient operations for insertion, deletion, and access. The operations and their complexities are outlined below:

### Operations on Arrays:

- **Insertion:** Inserting an element at the end of the array takes  $O(1)$  time on average. However, inserting at a specific index requires  $O(n)$  time, as elements may need to be shifted.
- **Deletion:** Deleting an element from the end of the array takes  $O(1)$ , but deleting from a specific index requires shifting elements, resulting in  $O(n)$ .
- **Access:** Accessing an element by index is done in  $O(1)$  time, as lists in Python support direct indexing.



```
1 class Array:
2     def __init__(self):
3         self.array = []
4
5     def insert(self, index, element):
6         """ Insert element at specified index """
7         self.array.insert(index, element)
8
9     def delete(self, index):
10        """ Delete element from specified index """
11        if 0 <= index < len(self.array):
12            del self.array[index]
13
14    def access(self, index):
15        """ Access element at specified index """
16        if 0 <= index < len(self.array):
17            return self.array[index]
18        return None
19
20    def display(self):
21        """ Display all elements in the array """
22        print(self.array)
23
24    class Matrix:
25        def __init__(self, rows, cols):
26            self.matrix = [[0 for _ in range(cols)] for _ in range(rows)]
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```

Stack Operations:  
[5, 10, 15]  
Pop element: 15

For **matrices**, we can represent them as lists of lists, where each element of the outer list is a row in the matrix.

```
1 class Array:
2
3     def display(self):
4         """ Display all elements in the array """
5         print(self.array)
6
7 class Matrix:
8     def __init__(self, rows, cols):
9         self.matrix = [[0 for _ in range(cols)] for _ in range(rows)]
10
11     def insert(self, row, col, value):
12         """ Insert value at matrix[row][col] """
13         if row < len(self.matrix) and col < len(self.matrix[0]):
14             self.matrix[row][col] = value
15
16     def access(self, row, col):
17         """ Access value at matrix[row][col] """
18         if row < len(self.matrix) and col < len(self.matrix[0]):
19             return self.matrix[row][col]
20         return None
21
22     def display(self):
23         """ Display the entire matrix """
24         for row in self.matrix:
25             print(row)
26
27 class Stack:
28
29 Stack Operations:
30 [5, 10, 15]
31 Pop element: 15
32 [5, 10]
```

## Stacks and Queues

A **stack** is a LIFO (Last In First Out) data structure, and a **queue** is a FIFO (First In First Out) data structure. Both stacks and queues can be implemented using arrays (or lists in Python).

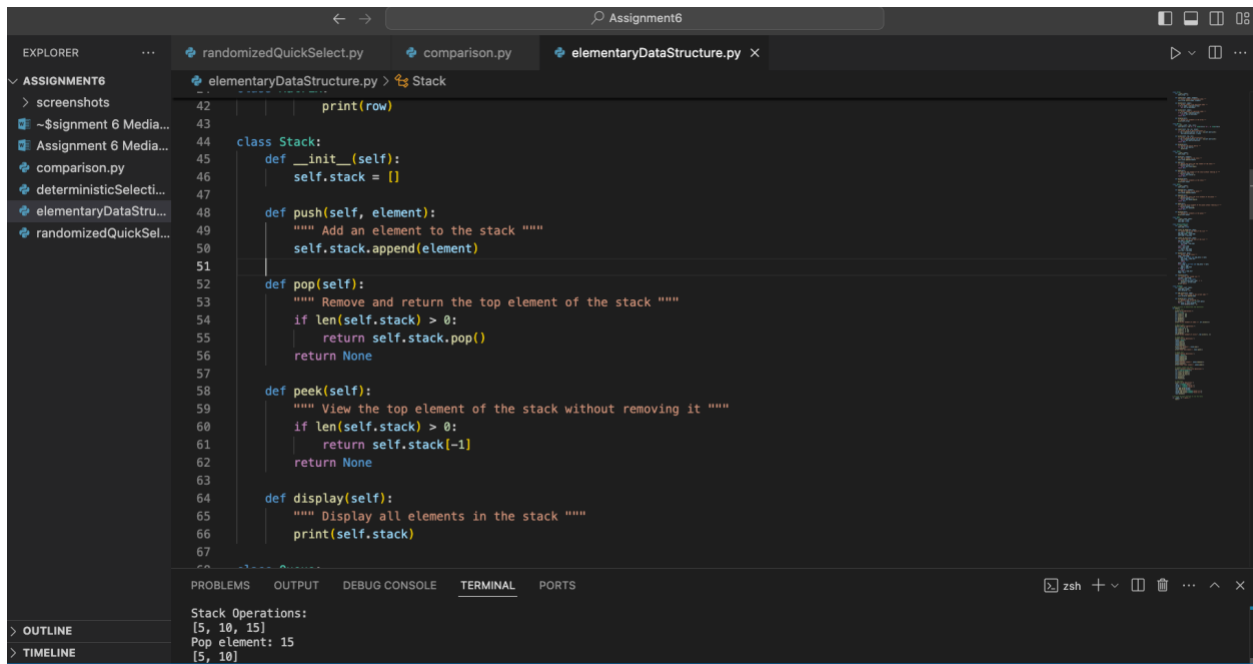
### Operations on Stacks:

- **Push:** Inserting an element at the end of the stack, which takes  $O(1)$  time.
- **Pop:** Removing the last element, also  $O(1)$ .
- **Peek:** Accessing the top element in constant time,  $O(1)$ .

### Operations on Queues:

- **Enqueue:** Adding an element to the end of the queue, which takes  $O(1)$ .
- **Dequeue:** Removing the first element, which takes  $O(1)$  on average, though it can be  $O(n)$  if using a list where elements are shifted.
- **Peek:** Accessing the first element,  $O(1)$ .

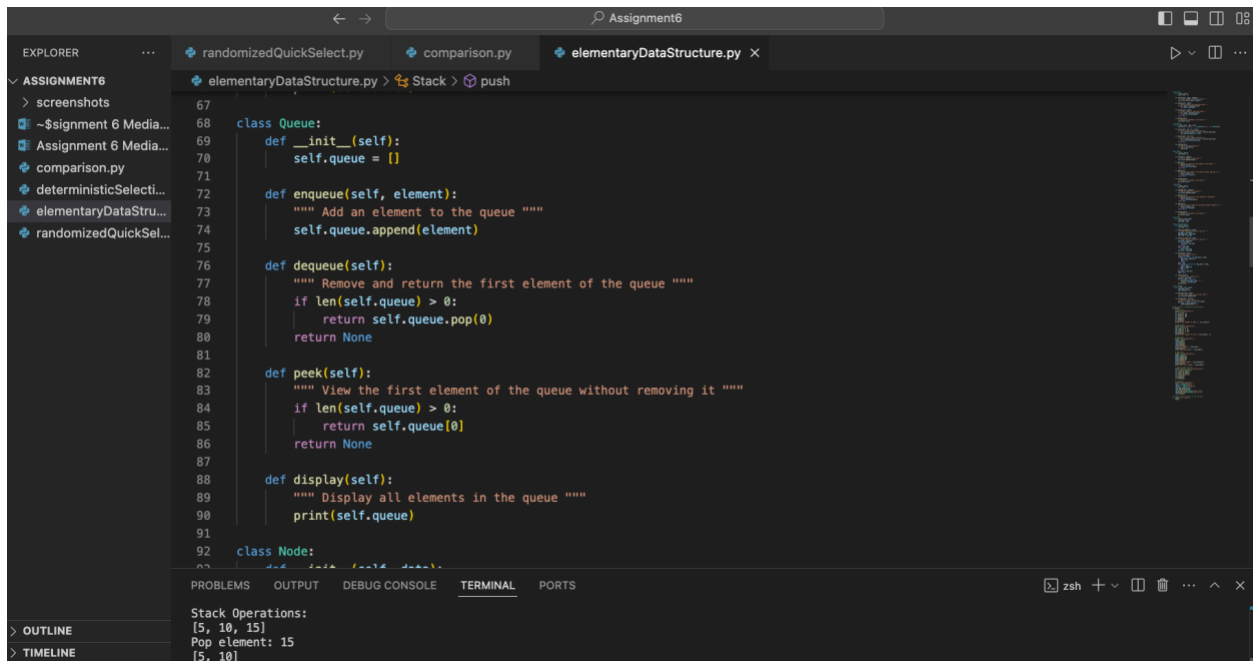
### Stack Implementation:



```
42     print(row)
43
44 class Stack:
45     def __init__(self):
46         self.stack = []
47
48     def push(self, element):
49         """ Add an element to the stack """
50         self.stack.append(element)
51
52     def pop(self):
53         """ Remove and return the top element of the stack """
54         if len(self.stack) > 0:
55             return self.stack.pop()
56         return None
57
58     def peek(self):
59         """ View the top element of the stack without removing it """
60         if len(self.stack) > 0:
61             return self.stack[-1]
62         return None
63
64     def display(self):
65         """ Display all elements in the stack """
66         print(self.stack)
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```

Stack Operations:  
[5, 10, 15]  
Pop element: 15  
[5, 10]

## Queue Implementation:



```
67
68 class Queue:
69     def __init__(self):
70         self.queue = []
71
72     def enqueue(self, element):
73         """ Add an element to the queue """
74         self.queue.append(element)
75
76     def dequeue(self):
77         """ Remove and return the first element of the queue """
78         if len(self.queue) > 0:
79             return self.queue.pop(0)
80         return None
81
82     def peek(self):
83         """ View the first element of the queue without removing it """
84         if len(self.queue) > 0:
85             return self.queue[0]
86         return None
87
88     def display(self):
89         """ Display all elements in the queue """
90         print(self.queue)
91
92
93 class Node:
94     def __init__(self, data):
95         self.data = data
96         self.next = None
97
98
99
100
```

Stack Operations:  
[5, 10, 15]  
Pop element: 15  
[5, 10]

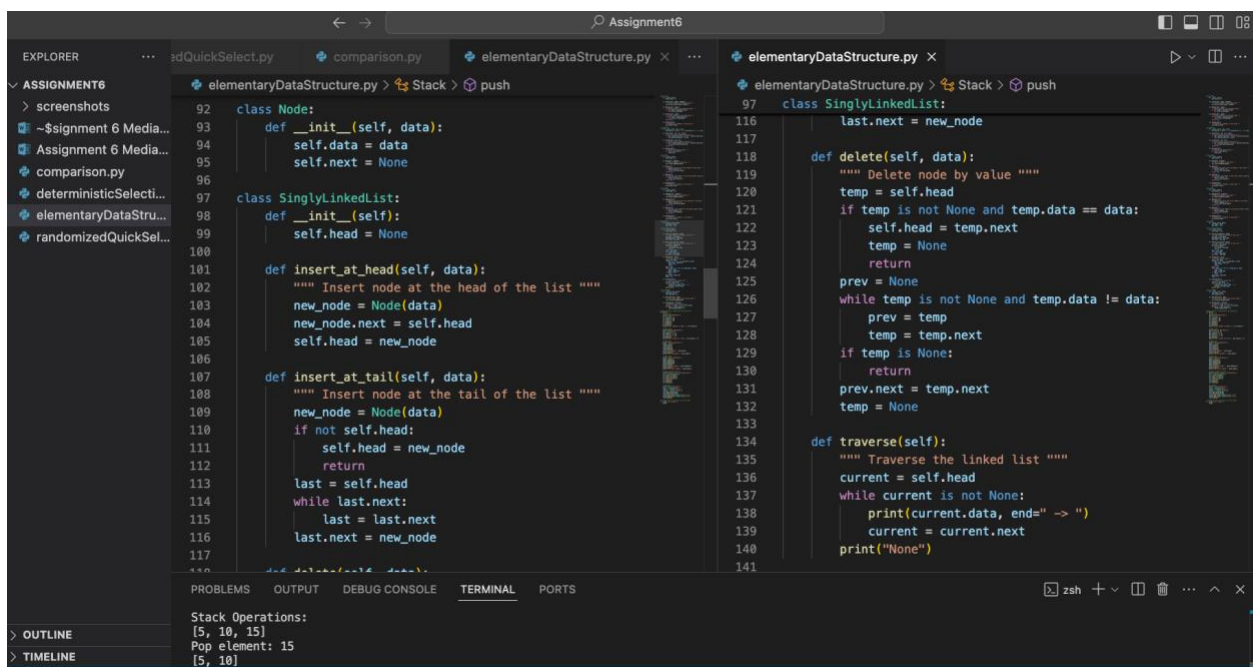
## Linked Lists

A **singly linked list** consists of nodes where each node contains an element and a reference to the next node in the list. The operations on a singly linked list include insertion, deletion, and traversal.

### Operations on Singly Linked Lists:

- **Insertion:** Inserting at the head or tail of the list is  $O(1)$ , but inserting at an arbitrary position requires traversing the list, making it  $O(n)$ .
- **Deletion:** Deletion at the head is  $O(1)$ , while deletion at an arbitrary position requires  $O(n)$ .
- **Traversal:** Traversing through the list is  $O(n)$  because each node needs to be accessed sequentially.

### Linked List Node Class and Operations:



The screenshot shows a code editor with two files open: `elementaryDataStructure.py` and `elementaryDataStructure.py`. The left file contains the `Node` class and the `SinglyLinkedList` class. The right file contains the `SinglyLinkedList` class. The `Node` class has an `__init__` method that takes `data` and sets `self.data = data` and `self.next = None`. The `SinglyLinkedList` class has an `__init__` method that sets `self.head = None`. It also has methods for `insert_at_head`, `insert_at_tail`, `delete`, and `traverse`. The `insert_at_head` method inserts a new node at the head of the list. The `insert_at_tail` method inserts a new node at the tail of the list. The `delete` method deletes a node by value. The `traverse` method traverses the linked list and prints the data of each node.

```
class Node:
    def __init__(self, data):
        self.data = data
        self.next = None

class SinglyLinkedList:
    def __init__(self):
        self.head = None

    def insert_at_head(self, data):
        """ Insert node at the head of the list """
        new_node = Node(data)
        new_node.next = self.head
        self.head = new_node

    def insert_at_tail(self, data):
        """ Insert node at the tail of the list """
        new_node = Node(data)
        if not self.head:
            self.head = new_node
            return
        last = self.head
        while last.next:
            last = last.next
        last.next = new_node

    def delete(self, data):
        """ Delete node by value """
        temp = self.head
        if temp is not None and temp.data == data:
            self.head = temp.next
            temp = None
            return
        prev = None
        while temp is not None and temp.data != data:
            prev = temp
            temp = temp.next
        if temp is None:
            return
        prev.next = temp.next
        temp = None

    def traverse(self):
        """ Traverse the Linked List """
        current = self.head
        while current is not None:
            print(current.data, end=" -> ")
            current = current.next
        print("None")
```

### Rooted Trees

A rooted tree is a tree where one node is considered the root, and all other nodes are its descendants. Each node can be represented using linked lists, where each node has a reference to its children.

```
134 class SinglyLinkedList:
135     def traverse(self):
136         current = self.head
137         while current is not None:
138             print(current.data, end=" ")
139             current = current.next
140         print("None")
141
142 class TreeNode:
143     def __init__(self, data):
144         self.data = data
145         self.children = []
146
147     def add_child(self, node):
148         """ Add a child node to the current node """
149         self.children.append(node)
150
151     def display(self, level=0):
152         """ Display tree structure """
153         print(" " * level * 2 + str(self.data))
154         for child in self.children:
155             child.display(level + 1)
156
157 # Main function to demonstrate the operations
158 def main():
159     # Array Test
160     print("Array Operations:")
```

Stack Operations:  
[5, 10, 15]  
Pop element: 15  
[5, 10]

```
158 def main():
184     stack.push(15)
185     stack.display()
186     print("Pop element:", stack.pop())
187     stack.display()
188     print("Peek top element:", stack.peek())
189
190 # Queue Test
191 print("\nQueue Operations:")
192 queue = Queue()
193 queue.enqueue(10)
194 queue.enqueue(20)
195 queue.enqueue(30)
196 queue.display()
197 print("Dequeue element:", queue.dequeue())
198 queue.display()
199 print("Peek front element:", queue.peek())
200
201 # Singly Linked List Test
202 print("\nSingly Linked List Operations:")
203 sll = SinglyLinkedList()
204 sll.insert_at_head(1)
205 sll.insert_at_tail(2)
206 sll.insert_at_tail(3)
207 sll.traverse()
208 sll.delete(2)
```

Stack Operations:  
[5, 10, 15]  
Pop element: 15  
[5, 10]

Output:

The screenshot shows a VS Code editor with a file named `elementaryDataStructure.py` open. The terminal window displays the output of running the script, which includes various data structure operations and their results:

```
(base) milanbista@Milans-MBP Assignment6 % python3 elementaryDataStructure.py
Array Operations:
[10, 20, 30]
[10, 30]
Access element at index 1: 30

Matrix Operations:
[5, 0, 0]
[0, 10, 0]
[0, 0, 15]
Access element at [1][1]: 10

Stack Operations:
[5, 10, 15]
Pop element: 15
[5, 10]
Peek top element: 10

Queue Operations:
[10, 20, 30]
Dequeue element: 10
[20, 30]
Peek front element: 20

Singly Linked List Operations:
1 -> 2 -> 3 -> None
1 -> 3 -> None

Tree Operations:
Root
  Child 1
    Child 1.1
  Child 2
    Child 2.1
```

## 2. Performance Analysis

- **Arrays:**
  - Insertion and deletion in the middle of the array takes  $O(n)$  time due to shifting of elements. Access by index is constant time,  $O(1)$ .
- **Stacks and Queues:**
  - Both stack and queue operations (push, pop, enqueue, dequeue) take  $O(1)$  time when implemented using arrays. However, using a list for queues can lead to  $O(n)$  complexity for dequeue operations due to shifting elements.
- **Linked Lists:**
  - Operations such as insertion and deletion at the head of a linked list are  $O(1)$ , but inserting or deleting at an arbitrary position is  $O(n)$  due to the need for traversal.
- **Rooted Trees:**

- Operations like insertion or deletion of a node in a rooted tree are  $O(1)$  when done at the root, but operations on non-root nodes require traversal, resulting in  $O(n)$  complexity.

#### Trade-offs:

- **Arrays vs Linked Lists:** Arrays offer constant-time access, but linked lists provide more efficient insertion and deletion at the head.
  - **Stacks and Queues:** Stacks are more efficient when using arrays due to  $O(1)$  push and pop operations. Queues can be more efficient with linked lists if dequeuing from the front is frequent.
- 

### 3. Discussion

#### Practical Applications:

- **Arrays** are best used when frequent random access to elements is required, such as in lookups or when the array size is fixed, and insertion/deletion is infrequent.
- **Stacks** are ideal for problems that require Last-In-First-Out (LIFO) behavior, such as recursive function calls, parsing expressions, and backtracking algorithms.
- **Queues** are often used in scenarios where First-In-First-Out (FIFO) behavior is needed, such as in scheduling tasks or handling data streams.
- **Linked Lists** are useful when the size of the data structure is unknown and frequently changing. They are often used in implementing dynamic data structures like queues, stacks, and adjacency lists for graph representations.
- **Rooted Trees** are effective in representing hierarchical data, such as file systems, organization structures, or decision trees.



Each data structure has its strengths and weaknesses, and the choice of which to use depends on the specific problem requirements, such as memory efficiency, access patterns, and the types of operations that need to be performed.

## **References**

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Knuth, D. E. (1998). *The art of computer programming, Volume 3: Sorting and searching* (2nd ed.). Addison-Wesley.