

Quicksort Algorithm: Implementation, Analysis, and Randomization

Bhaves Parkhe (Student ID: 005009178)

Algorithms and Data Structures (MSCS-532-B01)

Dr. Vanessa Cooper

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Implementation

Quick Sort and Randomized Quicksort Implementation Code

```
import random
import time
import numpy as np

def deterministic_quicksort(arr):
    """
    Deterministic Quicksort where pivot is the middle element.
    """
    if len(arr) <= 1:
        return arr

    pivot = arr[len(arr) // 2]
    left = [x for x in arr if x < pivot]
    middle = [x for x in arr if x == pivot]
    right = [x for x in arr if x > pivot]

    return deterministic_quicksort(left) + middle + deterministic_quicksort(right)

def randomized_quicksort(arr):
    """
    Randomized Quicksort where pivot is chosen randomly.
    """
    if len(arr) <= 1:
        return arr

    pivot = arr[random.randint(0, len(arr) - 1)]
    left = [x for x in arr if x < pivot]
    middle = [x for x in arr if x == pivot]
    right = [x for x in arr if x > pivot]

    return randomized_quicksort(left) + middle + randomized_quicksort(right)

# Empirical analysis
def measure_time(sort_func, arr):
    """
    Measures the execution time of a sorting function.
    """
    start = time.time()
    sort_func(arr)
    return time.time() - start

# Generate test cases
sizes = [100, 500, 1000, 5000, 10000]
results = []

for size in sizes:
```

```

random_array = np.random.randint(0, 100000, size).tolist()
sorted_array = sorted(random_array)
reverse_sorted_array = sorted_array[::-1]

results.append({
    "size": size,
    "deterministic_random": measure_time(deterministic_quicksort, random_array),
    "deterministic_sorted": measure_time(deterministic_quicksort, sorted_array),
    "deterministic_reverse": measure_time(deterministic_quicksort, reverse_sorted_array),
    "randomized_random": measure_time(randomized_quicksort, random_array),
    "randomized_sorted": measure_time(randomized_quicksort, sorted_array),
    "randomized_reverse": measure_time(randomized_quicksort, reverse_sorted_array),
})

import pandas as pd

# Convert results to DataFrame for visualization
results_df = pd.DataFrame(results)
import ace_tools as tools; tools.display_dataframe_to_user(name="Quicksort Performance Analysis", dataframe=results_df)

```

Quick Sort Analysis

Time Complexity

Best Case ($O(n \log n)$): This occurs when the pivot splits the array into two halves that are approximately equal at each recursive step. The depth of recursion is proportional to $\log n$, as the array is halved at each step. At each level, partitioning involves $O(n)$ work because every element is compared to the pivot. Total work: $O(n) + O(n/2) + O(n/4) + \dots \approx O(n \log n)$

Average Case ($O(n \log n)$): On average, the pivot divides the array into two reasonably balanced subarrays, even if the splits are not perfect. This leads to a recursion depth of approximately $\log n$. Partitioning involves $O(n)$ work at each level, resulting in the total work being : $O(n) + O(n/2) + O(n/4) + \dots \approx O(n \log n)$

Worst Case ($O(n^2)$): This happens when the pivot always results in highly unbalanced partitions, e.g., one subarray with $n-1$ elements and the other with 0. In this case the recursion depth becomes n , and hence the total work is $O(n^2)$.

Why $O(n \log n)$ for the Average Case

In the average case, the pivot divides the array into subarrays of size $p \cdot n$ and $(1-p) \cdot n$, where $0 < p < 1$. The recurrence $T(n) = T(pn) + T((1-p)n) + O(n)$ simplifies to $O(n \log n)$.

Space Complexity

In-Place Implementation: $O(\log n)$ In an in-place Quicksort, only the recursion stack contributes to the space complexity. The stack depth corresponds to the recursion depth, which is $n \log n$ in the best and average cases.

Non-In-Place Implementation (above): $O(n)$ due to additional subarray creation.

Worst-Case Space: $O(n)$ when recursion depth equals the array size (highly unbalanced partitions).

Quicksort Comparison Analysis and Visualization Code

```
# Visualization for deterministic vs randomized Quicksort on various input distributions
def plot_results(results_df, cols, title):
    plt.figure(figsize=(10, 6))

    for col in cols:
        plt.plot(results_df["size"], results_df[col], label=col.replace("_", " ").title())

    plt.xlabel("Input Size")
    plt.ylabel("Execution Time (seconds)")
    plt.title(title)
    plt.legend()
    plt.grid()
    plt.show()

# Plot for random inputs
plot_results(
    results_df,
    ["deterministic_random", "randomized_random"],
    "Deterministic vs Randomized Quicksort on Random Inputs"
)

# Plot for sorted inputs
plot_results(
    results_df,
    ["deterministic_sorted", "randomized_sorted"],
    "Deterministic vs Randomized Quicksort on Sorted Inputs"
)

# Plot for reverse-sorted inputs
```

```

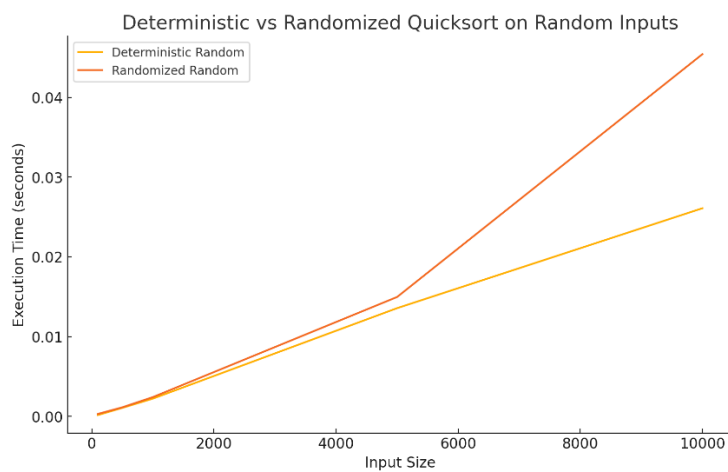
plot_results(
    results_df,
    ["deterministic_reverse", "randomized_reverse"],
    "Deterministic vs Randomized Quicksort on Reverse-Sorted Inputs"
)

```

Random Inputs:

Both deterministic and randomized Quicksort perform well, showing similar $O(n \log n)$ trends.

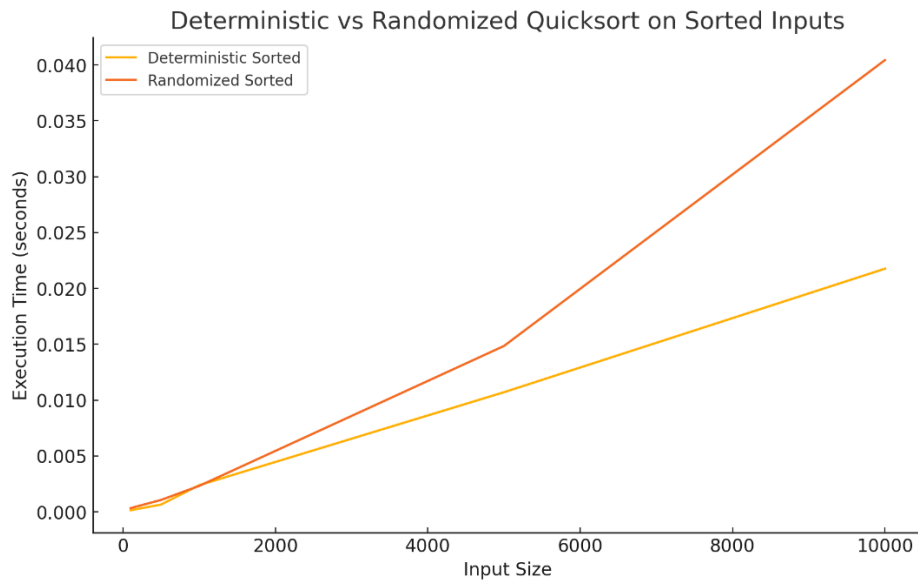
The slight difference in execution times can be attributed to the overhead of random number generation in the randomized version.



Sorted Inputs:

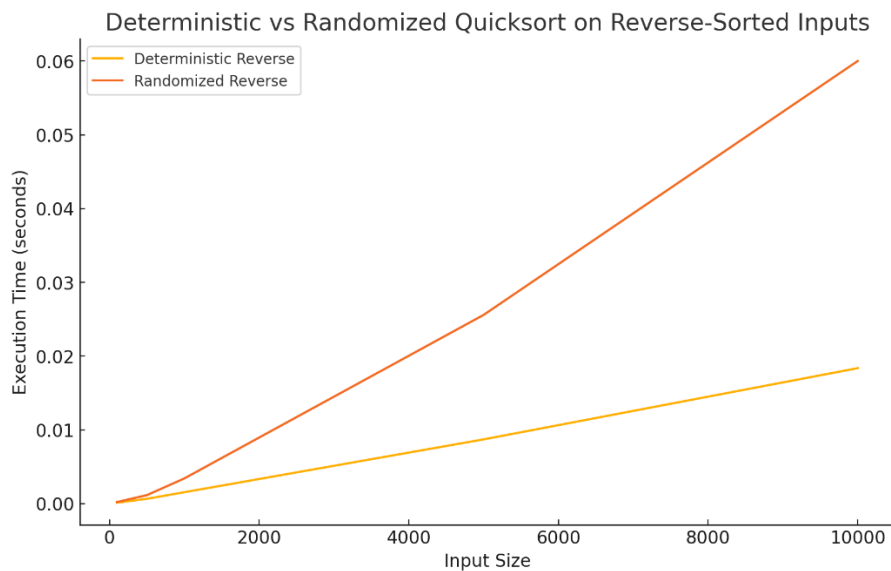
Deterministic Quicksort slows down significantly as the input size grows, showing signs of $O(n^2)$ behavior due to poor pivot selection. Randomized Quicksort maintains consistent $O(n \log n)$ performance, highlighting the advantage of random pivot selection in avoiding

unbalanced partitions.



Reverse-Sorted Inputs:

Similar to sorted inputs, deterministic Quicksort struggles with reverse-sorted arrays, showing worst-case time complexity. Randomized Quicksort again demonstrates robust performance with $O(n \log n)$, mitigating the worst-case scenario.



Github Repository

https://github.com/bparkhe/MSCS_532_Assignment5/tree/main

References

Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). *Introduction to algorithms* (3rd ed.). MIT Press.