1. Non-Recursive Program and Recursive Program

Q: What is the difference between a non-recursive and a recursive program?
A: In a **recursive program**, a function calls itself directly or indirectly to solve a smaller instance of the problem until it reaches a base case. This makes the recursive approach intuitive and often easier to write for problems like tree traversals, Fibonacci numbers, or factorial calculations. However, recursion can lead to increased memory usage because each recursive call adds to the system's call stack. If the recursion is deep, it could cause a stack overflow.

A **non-recursive (iterative) program**, on the other hand, uses loops (like `for` or `while`) to repeat calculations. Iterative solutions tend to use less memory as they don't require additional function calls or the call stack, making them more efficient in terms of space. For example, calculating Fibonacci numbers iteratively avoids the excessive overhead that comes with recursive calls.

Use Case Examples:

- Recursive: Depth-First Search (DFS), Fibonacci sequence.
- Non-recursive: Breadth-First Search (BFS), loops in sorting algorithms.

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2. Fibonacci Numbers

Q: What are Fibonacci numbers, and how are they defined?
A: The **Fibonacci sequence** is a series of numbers where each number is the sum of the two preceding ones, typically starting with 0 and 1. The Fibonacci sequence can be described by the recurrence relation:

F(0)=0,F(1)=1F(0) = 0, F(1) = 1F(0)=0,F(1)=1 F(n)=F(n−1)+F(n−2)for n≥2F(n) = F(n-1) + F(n-2) \quad \text{for} \, n \geq 2F(n)=F(n−1)+F(n−2)forn≥2

The sequence begins: 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, ...

Fibonacci numbers appear in nature, art, and computer science. In computational terms, recursive algorithms to calculate Fibonacci numbers have a time complexity of O(2^n) due to the repeated calculations of the same subproblems. Iterative solutions reduce the time complexity to O(n).

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3. Analysis of Time and Space Complexity

Q: What is time complexity, and how does it differ from space complexity?
A: Time complexity is a measure of the amount of time an algorithm takes to run as a function

of the input size (n). It helps to quantify the efficiency of an algorithm. Common time complexities include:

- **O(1)**: Constant time, independent of input size.
- **O(log n)**: Logarithmic time, often seen in binary search algorithms.
- **O(n)**: Linear time, where the time increases proportionally to the input size.
- **O(n log n)**: Time complexity for efficient sorting algorithms (e.g., merge sort, quicksort).
- **O(n²)**: Quadratic time, common in simple sorting algorithms (e.g., bubble sort).

Space complexity refers to the amount of memory an algorithm uses in relation to its input size. Like time complexity, space complexity can be constant, linear, logarithmic, etc. Recursive algorithms tend to have higher space complexity due to the call stack.

For example, recursive Fibonacci calculation has exponential time complexity (O(2^n)) and linear space complexity (O(n)) due to recursive stack calls, while the iterative version has linear time complexity (O(n)) and constant space complexity (O(1)).

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4. Huffman Encoding Using a Greedy Strategy

Q: What is Huffman encoding, and how does it use a greedy strategy?
A: Huffman encoding is a lossless data compression algorithm that assigns variable-length binary codes to input characters, with shorter codes assigned to more frequent characters. The algorithm constructs a binary tree where each character is a leaf node, and the path to each leaf defines the binary encoding.

The **greedy strategy** used by Huffman encoding is based on repeatedly choosing the two characters (or subtrees) with the lowest frequencies, combining them, and treating them as a single unit. This process is repeated until all characters are encoded, ensuring an optimal encoding that minimizes the overall length of the encoded message.

For example, if you have characters with frequencies {A:5, B:9, C:12, D:13, E:16, F:45}, Huffman encoding would combine the two lowest frequency characters (A and B), and repeat this process until a complete tree is built.

---

5. Greedy Strategy

Q: What is a greedy strategy in algorithms?
A: A **greedy algorithm** builds up a solution step by step, making the choice that looks best at each step (locally optimal choice) without reconsidering previously made decisions. The hope is that the locally optimal solutions will lead to a globally optimal solution.

Greedy algorithms are generally easier to implement and faster than other approaches like dynamic programming but may not always guarantee the optimal solution for every problem. However, they work perfectly for problems like Huffman encoding and the fractional knapsack problem.

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6. Fractional Knapsack Problem Using a Greedy Method

Q: How does the greedy method solve the fractional knapsack problem?
A: The **fractional knapsack problem** allows taking fractions of items. The greedy solution to this problem is based on selecting items in descending order of their value-to-weight ratio (profit density). The item with the highest ratio is selected first, then the next, until the knapsack is full.

In each step, if the entire item fits in the remaining capacity of the knapsack, it is added; otherwise, a fraction of it is taken. The process guarantees that the solution is optimal due to the greedy strategy's focus on maximizing value per unit weight.

Time complexity: O(n log n) due to the sorting of items by value-to-weight ratio.

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7. 0-1 Knapsack Problem Using Dynamic Programming or Branch and Bound

Q: What is the 0-1 knapsack problem, and how is it solved using dynamic programming?
A: The **0-1 knapsack problem** restricts you to either include an item or leave it out (no fractions allowed). Given a set of items, each with a weight and value, the goal is to maximize the total value without exceeding the weight capacity.

Dynamic programming solves the 0-1 knapsack problem by building a table (matrix) that records the maximum value obtainable for each subproblem (i.e., for each weight limit from 0 to the knapsack capacity and for each item). The final cell in the table provides the optimal solution.

Time complexity: O(nW), where n is the number of items and W is the capacity of the knapsack.

---

8. Dynamic Programming Approach

Q: What is dynamic programming?
A: Dynamic programming is an optimization technique used to solve problems by breaking them down into overlapping subproblems, solving each subproblem once, and storing their solutions (in a table) to avoid redundant work. Dynamic programming is particularly useful for problems with optimal substructure and overlapping subproblems, like the 0-1 knapsack and shortest path problems (e.g., Floyd-Warshall algorithm).

Examples:

- **0-1 knapsack problem**.
- **Longest common subsequence**.
- **Matrix chain multiplication**.

---

9. Branch and Bound Strategy

Q: What is the branch and bound strategy?
A: Branch and bound is a general algorithmic framework used for solving combinatorial optimization problems like the traveling salesperson problem and the 0-1 knapsack problem. It systematically explores the solution space by dividing it into smaller subproblems (branching) and calculating upper or lower bounds to prune suboptimal solutions (bounding).

In branch and bound, each subproblem (or "branch") is evaluated, and parts of the search space that cannot contain an optimal solution are eliminated ("bounded"). This approach reduces the computational complexity by focusing only on promising paths.

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10. N-Queens Problem

Q: What is the N-Queens problem?
A: The **N-Queens problem** is a classic combinatorial problem where `N` queens must be placed on an `N x N` chessboard such that no two queens threaten each other. This means no two queens can share the same row, column, or diagonal.

The problem is solved using backtracking, which systematically explores possible placements of queens and backtracks if a placement leads to a conflict.

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11. N-Queens Problem Using Backtracking

Q: How does backtracking solve the N-Queens problem?
A: Backtracking is an algorithmic technique for solving constraint satisfaction problems like N-Queens. The idea is to place queens one by one in different rows and columns, ensuring no conflicts with already placed queens. If placing a queen in a row leads to a conflict later, the algorithm backtracks by removing the queen and trying the next available position.

Backtracking ensures that all possibilities are explored, but it avoids redundant work by abandoning partial solutions that cannot lead to a valid solution (i.e., early pruning).

12. Analysis of Quicksort: Deterministic and Randomized

Q: What is the difference between deterministic and randomized Quicksort?
A: Deterministic Quicksort chooses a fixed pivot (e.g., the first, last, or middle element) for partitioning the array, whereas **randomized Quicksort** chooses the pivot element randomly. The goal of randomization is to reduce the likelihood of encountering the worst-case scenario, which can occur when the pivot divides the array unevenly, leading to $O(n^2)$ time complexity.

Randomized Quicksort has an expected time complexity of O(n log n), and by selecting random pivots, it mitigates the effects of bad pivot choices, ensuring better average-case performance.

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13. Analysis of Matrix Multiplication Using Multithreading

Q: How does multithreaded matrix multiplication improve performance?
A: In **multithreaded matrix multiplication**, computations are parallelized to improve performance. Two common approaches are:

1. **One thread per row:** Each thread is responsible for computing the elements of one row of the result matrix.
2. **One thread per cell:** Each thread calculates a single element of the result matrix, leading to maximum parallelism.

By distributing the workload across multiple threads, the time taken to multiply large matrices can be significantly reduced, especially on multicore processors.

Performance analysis involves measuring the speedup achieved by multithreading and the efficiency of resource usage (cores and memory).

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14. Analysis of Merge Sort and Multithreaded Merge Sort

Q: What is the time complexity of Merge Sort in the best and worst cases?
A: Merge Sort has a time complexity of O(n log n) in both the best and worst cases. This is because even in the best case (when the input array is already sorted), the algorithm still divides the array and performs merging operations.

In **multithreaded Merge Sort**, the array can be split into smaller subarrays and sorted concurrently by different threads. This reduces the overall runtime on multicore systems, although the merging step may still pose a bottleneck due to its sequential nature.

---

15. Naive String Matching Algorithm

Q: What is the Naive String Matching algorithm?
A: The **Naive String Matching algorithm** is a straightforward approach to finding occurrences of a pattern in a text. It compares the pattern to each possible substring of the text, one by one. The algorithm slides the pattern over the text and checks for a match at every position.

Time complexity: O(mn), where `m` is the length of the pattern and `n` is the length of the text. This is inefficient for large inputs or long patterns.

---

16. Rabin-Karp Algorithm for String Matching

Q: How does the Rabin-Karp algorithm work for string matching?
A: The **Rabin-Karp algorithm** improves upon the naive approach by using hashing to compare the pattern with substrings of the text. Instead of comparing the entire pattern character by character, Rabin-Karp computes a hash value for the pattern and compares it with the hash values of the text substrings.

If the hash values match, the algorithm checks the actual characters to confirm a match. This allows for faster average-case performance, especially when searching for multiple patterns.

Time complexity: O(n + m) on average, where `n` is the length of the text and `m` is the length of the pattern.

---

17. Comparison: Naive String Matching and Rabin-Karp Algorithm

Q: What is the main difference between the Naive and Rabin-Karp algorithms?
A: The **Naive algorithm** compares each substring of the text with the pattern, while the **Rabin-Karp algorithm** uses hashing to speed up comparisons. The Naive algorithm has a worst-case time complexity of O(mn), while Rabin-Karp improves the average-case time complexity to O(n + m) by minimizing redundant character comparisons.

Rabin-Karp is particularly useful for multiple pattern matching, while the Naive approach is simple but inefficient for larger inputs.

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18. Exact vs Approximation Algorithms for TSP

Q: What is the difference between exact and approximation algorithms for the Travelling Salesperson Problem (TSP)?

A: In the **Travelling Salesperson Problem (TSP)**, the goal is to find the shortest possible route that visits a set of cities and returns to the starting point. An **exact algorithm** guarantees finding the optimal solution but can be computationally expensive, with time complexity O(n!). Examples include dynamic programming and branch and bound methods.

Approximation algorithms, on the other hand, provide near-optimal solutions in polynomial time. These algorithms trade accuracy for efficiency and are used when finding the exact solution is impractical for large inputs. For example, a heuristic approach like nearest-neighbor can quickly provide a reasonable solution but might not always be optimal.

---

19. Difference Between Greedy and Dynamic Programming Approaches

Q: How do greedy algorithms differ from dynamic programming?
A: Greedy algorithms make locally optimal choices at each step with the hope that these choices lead to a globally optimal solution. They are simpler and faster but may not always guarantee the best result for all problems. Greedy algorithms work well for problems like Huffman encoding and the fractional knapsack problem.

Dynamic programming, on the other hand, solves problems by breaking them down into overlapping subproblems, solving each subproblem only once, and storing the results. Dynamic programming guarantees an optimal solution but is typically more complex and slower than greedy algorithms.

---

20. Difference Between Backtracking and Branch & Bound

Q: What is the difference between backtracking and branch and bound?
A: Backtracking is a general problem-solving technique where you incrementally build candidates for the solution and backtrack as soon as a candidate is invalid. It's typically used for constraint satisfaction problems like the N-Queens problem and maze solving. Backtracking exhaustively searches for solutions but prunes paths that cannot possibly lead to valid solutions.

Branch and bound is a more advanced technique used for optimization problems. It systematically explores subproblems (branching) and uses upper or lower bounds to prune sections of the search space that cannot improve the current best solution. This method is typically used for solving combinatorial optimization problems like the 0-1 knapsack problem or the traveling salesperson problem.

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21. P, NP, NP-Complete, and NP-Hard Problems

Q: What are P, NP, NP-complete, and NP-hard problems?
A:

- **P** (Polynomial time) refers to problems that can be solved by a deterministic algorithm in polynomial time, e.g., sorting algorithms.
- **NP** (Nondeterministic Polynomial time) problems are those where a given solution can be verified in polynomial time, but it's unknown whether they can be solved in polynomial time.
- **NP-complete** problems are the hardest problems in NP. If any NP-complete problem can be solved in polynomial time, then every problem in NP can also be solved in polynomial time. An example is the Traveling Salesperson Problem (TSP).
- **NP-hard** problems are at least as hard as NP-complete problems but don't necessarily belong to NP (e.g., they may not have a solution verifiable in polynomial time). An example is the Halting Problem.

---

22. Big O, Omega, and Theta Notations

Q: What is the difference between Big O, Omega, and Theta notations?
A: These notations are used to describe the asymptotic behavior of an algorithm's time or space complexity:

- **Big O (O)** describes the **upper bound** of an algorithm, indicating the worst-case scenario.
    - Example: $O(n^2)$ for bubble sort.
- **Omega (Ω)** describes the **lower bound**, indicating the best-case scenario.
    - Example: $\Omega(n)$ for linear search.
- **Theta (Θ)** describes the **tight bound**, indicating both the upper and lower bounds. It describes the exact performance of the algorithm for large input sizes.
    - Example: $\Theta(n \log n)$ for merge sort.

---

23. Reducibility

Q: What is reducibility in computational theory?
A: Reducibility refers to transforming one problem into another problem in such a way that a solution to the second problem gives a solution to the first. If problem A can be reduced to problem B, and if we know how to solve problem B, we can also solve problem A. Reducibility is a key concept in proving that certain problems belong to complexity classes like NP-complete.

For example, if you can reduce the TSP to another NP-complete problem, it means solving that other problem also solves the TSP. This is used in computational complexity to demonstrate the hardness of problems.

1. Divide and Conquer Strategy

Q: What is the divide and conquer strategy, and which problems can be solved using it?
A: Divide and conquer is a powerful algorithmic paradigm where a problem is broken down into smaller subproblems that are solved independently. The solutions to the subproblems are then combined to solve the original problem. The most famous examples include:

- **Merge Sort**: Divides the array into halves, sorts each half recursively, and then merges the sorted halves.
- **Quicksort**: Divides the array based on a pivot, recursively sorts the partitions, and combines the results.
- **Binary Search**: Divides the search space into halves and checks one half in each step.

Time complexity of divide and conquer algorithms depends on the number of divisions and the time to combine the results. For instance, Merge Sort has a time complexity of O(n log n), where n is the input size.

---

2. Master Theorem for Divide and Conquer Recurrences

Q: What is the Master Theorem, and how is it used to solve recurrences?
A: The **Master Theorem** provides a way to analyze the time complexity of divide-and-conquer algorithms by solving recurrence relations of the form:

T(n)=aT(nb)+O(nd)T(n) = aT\left(\frac{n}{b}\right) + O(n^d)T(n)=aT(bn)+O(nd)

Where:

- **a** is the number of subproblems,
- **b** is the factor by which the problem size is divided,
- **n^d** is the time complexity of the combining process.

The Master Theorem helps determine the time complexity in three cases:

1. **If log_b(a) > d**, time complexity is O(n^log_b(a)).
2. **If log_b(a) = d**, time complexity is O(n^d log n).
3. **If log_b(a) < d**, time complexity is O(n^d).

This theorem simplifies the analysis of common divide-and-conquer algorithms such as Merge Sort, Binary Search, and others.

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3. Greedy vs. Dynamic Programming

Q: What are the key differences between greedy algorithms and dynamic programming?
A: Both **greedy** algorithms and **dynamic programming** solve optimization problems but differ in approach:

- **Greedy algorithms** make the locally optimal choice at each step, hoping to find a global optimum. Greedy algorithms are simple and efficient but may not always provide an optimal solution for all problems. For example, the **Fractional Knapsack Problem** is optimally solved using a greedy approach.
- **Dynamic programming** solves problems by breaking them down into overlapping subproblems and storing their solutions. It guarantees an optimal solution by exploring all possibilities, making it more suitable for problems like the **0-1 Knapsack Problem**, **Longest Common Subsequence (LCS)**, or **Matrix Chain Multiplication**.

Time complexity for dynamic programming solutions is generally higher than greedy algorithms, but dynamic programming guarantees an optimal solution.

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4. Amortized Analysis

Q: What is amortized analysis, and how is it different from average-case analysis?
A: Amortized analysis looks at the average performance of an algorithm over a sequence of operations, ensuring that the cost of expensive operations is spread out across many cheaper operations. This method guarantees the average cost of operations, even though some individual operations may be costly.

For example, in **dynamic array resizing** (like in a `vector` or `ArrayList`), appending elements may involve a costly operation when the array resizes. However, the cost of resizing is distributed across many insertions, resulting in an **amortized constant time** O(1) for insertion.

Average-case analysis, on the other hand, evaluates the performance based on an expected input distribution and is typically more complex as it depends on the nature of the inputs.

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5. Graph Traversal: BFS vs. DFS

Q: What is the difference between Breadth-First Search (BFS) and Depth-First Search (DFS) in graph traversal?
A: BFS and **DFS** are fundamental graph traversal algorithms:

- **BFS** explores all vertices at the present depth level before moving on to vertices at the next depth level. BFS uses a **queue** data structure and is suitable for finding the shortest path in an unweighted graph. Time complexity: O(V + E), where V is the number of vertices and E is the number of edges.

- **DFS** explores as far as possible along each branch before backtracking. It uses a **stack** (or recursion) and is useful for detecting cycles, connected components, and topological sorting in graphs. Time complexity: O(V + E).

BFS is better for finding the shortest path in unweighted graphs, while **DFS** is useful in applications like topological sorting, solving mazes, or depth exploration of a problem space.

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6. Dijkstra's Algorithm vs. Bellman-Ford Algorithm

Q: How does Dijkstra's algorithm differ from the Bellman-Ford algorithm?
A: Both **Dijkstra's** and **Bellman-Ford** algorithms are used for finding the shortest paths in weighted graphs, but they differ in the following ways:

- **Dijkstra's Algorithm** works efficiently with **non-negative** weights and uses a **priority queue** to select the next closest vertex. It has a time complexity of O((V + E) log V) using a binary heap. Dijkstra's algorithm does not handle negative weight edges.
- **Bellman-Ford Algorithm** works even with **negative weights** and can detect negative weight cycles in the graph. It relaxes all edges repeatedly and has a time complexity of O(VE). While slower, Bellman-Ford is more versatile and can be applied to a wider range of problems.

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7. NP-Complete Problems

Q: What are NP-Complete problems, and why are they important?
A: NP-Complete problems are a subset of NP problems (nondeterministic polynomial time) that are both in NP and as hard as any other problem in NP. If an algorithm can be found to solve any NP-complete problem in polynomial time, then all NP problems can be solved in polynomial time (i.e., P = NP). NP-Complete problems are important because they help understand the limits of algorithmic efficiency and problem-solving.

Examples of NP-Complete problems include:

- **Travelling Salesperson Problem (TSP)**.
- **Knapsack Problem** (0-1 version).
- **3-SAT** (Boolean satisfiability problem).

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8. Heaps and Heapsort

Q: What is a heap, and how is heapsort implemented?
A: A **heap** is a specialized tree-based data structure that satisfies the **heap property**: in a max-heap, for any given node `i`, the value of `i` is greater than or equal to the values of its children. In a min-heap, the value of `i` is less than or equal to the values of its children.

Heapsort is a comparison-based sorting algorithm that uses a binary heap to sort an array. It first builds a max-heap from the array and repeatedly extracts the maximum element from the heap, placing it at the end of the array.

Time complexity: O(n log n), where n is the number of elements.

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9. Kruskal's Algorithm vs. Prim's Algorithm for Minimum Spanning Tree

Q: What are the differences between Kruskal's and Prim's algorithms for finding a minimum spanning tree?
A: Both **Kruskal's** and **Prim's** algorithms are greedy algorithms used to find a **Minimum Spanning Tree (MST)**, but they work differently:

- **Kruskal's Algorithm** sorts all the edges in increasing order and adds edges to the MST one by one, provided they do not form a cycle (using union-find to check for cycles). It's more suited for **sparse graphs** and has a time complexity of O(E log E), where E is the number of edges.
- **Prim's Algorithm** starts from an arbitrary node and grows the MST by adding the smallest edge that connects a vertex in the MST to a vertex outside the MST. It's more efficient for **dense graphs** and has a time complexity of $O(V^2)$ or O((V + E) log V) with priority queues.

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10. Approximation Algorithms

Q: What are approximation algorithms, and when are they used?
A: Approximation algorithms are used for solving NP-hard problems where finding an exact solution is computationally infeasible. These algorithms provide solutions that are close to the optimal solution within a guaranteed bound. Approximation algorithms trade off precision for efficiency, offering solutions in polynomial time.

For example, for the **Travelling Salesperson Problem (TSP)**, a simple heuristic like **nearest neighbor** provides an approximation, although it doesn't guarantee the optimal path. Another example is the **Vertex Cover Problem**, where approximation algorithms provide a cover with a size at most twice the optimal size.

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11. The Floyd-Warshall Algorithm

Q: What is the Floyd-Warshall algorithm, and what is its time complexity?
A: The **Floyd-Warshall algorithm** is an all-pairs shortest path algorithm that computes the shortest paths between every pair of vertices in a graph. It is particularly useful for dense graphs and can handle both negative and positive weights, provided there are no negative weight cycles.

The algorithm uses dynamic programming to iteratively improve the solution by considering whether a path through an intermediate vertex offers a shorter route between two vertices.

Time complexity: $O(V^3)$, where V is the number of vertices.

These questions offer an in-depth exploration of core algorithm concepts that BE Computer Engineering students are likely to encounter in their design and analysis of algorithms course. They not only cover basic principles but also advanced problem-solving techniques essential for competitive programming and real-world applications.

1. Fibonacci Numbers (Non-recursive and Recursive)

Oral Questions:

1. **Q:** What is the base case in the recursive Fibonacci function? **A:** The base case occurs when `n == 0` or `n == 1`, where the function directly returns the value of `n`.
2. **Q:** How does the time complexity of the recursive Fibonacci approach grow as `n` increases? **A:** The time complexity grows exponentially, O(2^n), because each function call spawns two more recursive calls for `n-1` and `n-2`.
3. **Q:** What is memoization, and how can it be used to optimize the recursive Fibonacci approach? **A:** Memoization is a technique where previously calculated results are stored and reused to avoid redundant calculations, reducing the time complexity from O(2^n) to O(n).
4. **Q:** How does the space complexity differ between the recursive and non-recursive Fibonacci approaches? **A:** The recursive approach has O(n) space complexity due to the call stack, while the non-recursive approach has O(1) space complexity because it only uses a few variables.
5. **Q:** What is the significance of the Fibonacci sequence in real-world applications? **A:** The Fibonacci sequence appears in various areas, including nature (e.g., the arrangement of leaves), computer algorithms (e.g., dynamic programming problems), and financial markets.

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2. Huffman Encoding using a Greedy Strategy

Oral Questions:

1. **Q:** Why is Huffman encoding considered a greedy algorithm? **A:** It builds an optimal prefix-free code by always choosing the two smallest frequency symbols at each step, ensuring an optimal solution for minimizing the overall code length.
2. **Q:** What data structure is commonly used to implement Huffman encoding efficiently? **A:** A min-heap or priority queue is used to efficiently select the two smallest frequency nodes at each step.
3. **Q:** How is Huffman encoding applied in data compression? **A:** Huffman encoding generates shorter codes for more frequent characters, thereby reducing the overall size of the encoded data.
4. **Q:** What does it mean for a Huffman code to be "prefix-free"? **A:** A prefix-free code means that no code is a prefix of any other code, ensuring that the encoded message can be uniquely decoded without ambiguity.
5. **Q:** What is the time complexity of building a Huffman tree? **A:** The time complexity is O(n log n), where n is the number of unique symbols, due to the use of the priority queue.

---

3. Fractional Knapsack Problem using a Greedy Method

Oral Questions:

1. **Q:** What is the key difference between the fractional knapsack and 0-1 knapsack problems? **A:** In the fractional knapsack problem, you can take fractions of an item, while in the 0-1 knapsack problem, you must take the whole item or none at all.
2. **Q:** Why is a greedy algorithm optimal for solving the fractional knapsack problem? **A:** Because you can always choose the item with the highest value-to-weight ratio first, and fractional items are allowed, making the greedy choice optimal.
3. **Q:** What is the time complexity of the greedy algorithm for the fractional knapsack problem? **A:** The time complexity is O(n log n) due to sorting the items based on their value-to-weight ratio.
4. **Q:** Can you solve the 0-1 knapsack problem using a greedy algorithm? **A:** No, the greedy algorithm does not always provide an optimal solution for the 0-1 knapsack problem because you cannot take fractions of items.
5. **Q:** How is the fractional knapsack problem used in resource allocation? **A:** It is used when resources are divisible, such as in financial investments, where a fraction of an asset can be chosen to maximize profit.

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4. 0-1 Knapsack Problem using Dynamic Programming or Branch and Bound

Oral Questions:

1. **Q:** What is the difference between the dynamic programming and branch and bound approaches to solving the 0-1 knapsack problem? **A:** Dynamic programming solves the problem by building a table of subproblems, while branch and bound explores a search tree, pruning branches that cannot lead to an optimal solution.
2. **Q:** What is the time complexity of solving the 0-1 knapsack problem using dynamic programming? **A:** The time complexity is O(nW), where `n` is the number of items and `W` is the knapsack capacity.
3. **Q:** How does the dynamic programming approach ensure an optimal solution for the 0-1 knapsack problem? **A:** It solves smaller subproblems and builds up to the overall problem, ensuring that all possible combinations of items are considered.
4. **Q:** What is the role of the state table (DP table) in dynamic programming for the knapsack problem? **A:** The DP table stores the maximum value that can be obtained with a given number of items and a given capacity, helping to avoid redundant calculations.
5. **Q:** In which real-world applications is the 0-1 knapsack problem used? **A:** It is used in resource allocation, budget management, and decision-making scenarios where choices must be made under a fixed set of constraints.

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5. N-Queens Problem using Backtracking

Oral Questions:

1. **Q:** What is the backtracking approach to solving the N-Queens problem? **A:** Backtracking places queens on the board incrementally, and if a conflict arises, it "backtracks" by removing the last placed queen and trying a different position.
2. **Q:** How do you check if a queen can be safely placed on the board? **A:** You check the row, column, and both diagonals to ensure no other queen is in a position to attack the current placement.
3. **Q:** What is the time complexity of solving the N-Queens problem using backtracking? **A:** The time complexity is O(N!), where `N` is the number of queens, because in the worst case, all possible placements must be explored.
4. **Q:** Why is the N-Queens problem considered a constraint satisfaction problem? **A:** It involves placing queens under the constraint that no two queens can threaten each other, which requires careful checking of each placement.
5. **Q:** What are some real-world applications of backtracking algorithms? **A:** Backtracking is used in solving puzzles like Sudoku, pathfinding, and constraint satisfaction problems in areas like scheduling and circuit design.

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6. Quicksort: Deterministic and Randomized Variants

Oral Questions:

1. **Q:** What is the key difference between the deterministic and randomized versions of Quicksort? **A:** In deterministic Quicksort, the pivot is chosen in a fixed way (e.g., last element), whereas in randomized Quicksort, the pivot is chosen randomly to avoid worst-case scenarios.
2. **Q:** Why is randomized Quicksort often preferred in practice over the deterministic version? **A:** Randomized Quicksort reduces the likelihood of encountering the worst-case time complexity ($O(n^2)$) by randomly selecting pivots, leading to better average performance.
3. **Q:** What is the average-case and worst-case time complexity of Quicksort? **A:** The average-case time complexity is $O(n \log n)$, while the worst-case time complexity is $O(n^2)$.
4. **Q:** How does Quicksort perform compared to other sorting algorithms like Merge Sort and Heap Sort? **A:** Quicksort is generally faster in practice due to its in-place sorting and better cache performance, though it has a worse worst-case time complexity compared to Merge Sort.
5. **Q:** How does the partitioning strategy in Quicksort affect its performance? **A:** The performance of Quicksort depends on how well the partitioning divides the array. A well-balanced partition leads to $O(n \log n)$ time complexity, while unbalanced partitions lead to $O(n^2)$.