



Big O Notation Basics

Common Time Complexities

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| $O(1)$ - Constant | Execution time is independent of input size. Example: Accessing an element in an array by index. |
| $O(\log n)$ - Logarithmic | Execution time increases logarithmically with input size. Example: Binary search. |
| $O(n)$ - Linear | Execution time increases linearly with input size. Example: Looping through an array. |
| $O(n \log n)$ - Loglinear | Execution time is a combination of linear and logarithmic. Example: Merge sort, quicksort (average case). |
| $O(n^2)$ - Quadratic | Execution time increases quadratically with input size. Example: Nested loops. |
| $O(2^n)$ - Exponential | Execution time doubles with each addition to the input data set. Example: Recursive Fibonacci calculation. |
| $O(n!)$ - Factorial | Execution time grows factorially with input size. Example: Traveling Salesman Problem (brute force). |

Understanding Big O

Big O notation describes the **upper bound** of an algorithm's time complexity. It focuses on the worst-case scenario and ignores constant factors and lower-order terms.

When analyzing algorithms, we care about how the execution time grows as the input size increases. Big O helps us compare the scalability of different algorithms.

Analyzing Code for Time Complexity

Basic Operations

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| Arithmetic Operations (+, -, *, /) | $O(1)$ |
| Variable Assignment | $O(1)$ |
| Array Indexing | $O(1)$ |

Control Structures

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| Simple for loop (iterating n times) | $O(n)$ |
| Nested for loops (iterating n times each) | $O(n^2)$ |
| while loop (dependent on input size) | Determined by the condition. Could be $O(n)$, $O(\log n)$, etc. |
| if-else statements | The complexity is determined by the most complex branch. |

Function Calls

The time complexity of a function call is the time complexity of the function being called. Be mindful of recursive calls!

Example: If `foo()` has a time complexity of $O(n)$, then calling `foo()` in your code adds $O(n)$ to the overall complexity.

Data Structures and Time Complexity

Common Data Structure Operations

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| Array Access (by index) | $O(1)$ |
| Array Search (unsorted) | $O(n)$ |
| Sorted Array Search (Binary Search) | $O(\log n)$ |
| Linked List Access (by index) | $O(n)$ |
| Hash Table Insertion/Deletion/Access (average case) | $O(1)$ |
| Binary Search Tree Insertion/Deletion/Search (average case) | $O(\log n)$ |
| Heap (min/max) Insertion/Deletion/Access | $O(\log n)$ |

Tips and Best Practices

General Advice

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| Always consider the worst-case scenario when determining time complexity. |
| Ignore constant factors and lower-order terms. $O(2n)$ is simplified to $O(n)$ and $O(n^2 + n)$ is simplified to $O(n^2)$. |
| Understand the underlying data structures and algorithms being used. This is crucial for accurate analysis. |
| Practice analyzing code snippets to improve your ability to quickly determine time complexity. |
| When asked about time complexity in an interview, explain your reasoning clearly and concisely. |

Amortized Analysis

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| <p>Amortized analysis is a method for analyzing the time complexity of an algorithm that performs a sequence of operations. It averages the time taken over a sequence of operations, even if some operations are very expensive.</p> <p>Example: Dynamic arrays (like ArrayList in Java or vector in C++) have $O(1)$ amortized time complexity for adding elements, even though resizing the array takes $O(n)$ time.</p> |
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