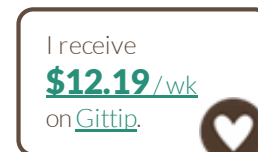


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# Know Thy Complexities!

Hi there! This webpage covers the space and time Big-O complexities of common algorithms used in Computer Science. When preparing for technical interviews in the past, I found myself spending hours crawling the internet putting together the best, average, and worst case complexities for search and sorting algorithms so that I wouldn't be stumped when asked about them. Over the last few years, I've interviewed at several Silicon Valley startups, and also some bigger companies, like Yahoo, eBay, LinkedIn, and Google, and each time that I prepared for an interview, I thought to myself "Why oh why hasn't someone created a nice Big-O cheat sheet?". So, to save all of you fine folks a ton of time, I went ahead and created one. Enjoy!

Good Fair Poor

## Searching

Algorithm

Data Structure

Time Complexity

Space  
Complexity

		Average	Worst	Worst
<a href="#">Depth First Search (DFS)</a>	Graph of  V  vertices and  E  edges -		$O( E  +  V )$	$O( V )$
<a href="#">Breadth First Search (BFS)</a>	Graph of  V  vertices and  E  edges -		$O( E  +  V )$	$O( V )$
<a href="#">Binary search</a>	Sorted array of n elements	$O(\log(n))$	$O(\log(n))$	$O(1)$
<a href="#">Linear (Brute Force)</a>	Array	$O(n)$	$O(n)$	$O(1)$
<a href="#">Shortest path by Dijkstra using a Min-heap as priority queue</a>	Graph with  V  vertices and  E  edges	$O(( V  +  E ) \log  V )$	$O(( V  +  E ) \log  V )$	$O( V )$
<a href="#">Shortest path by Dijkstra using an unsorted array as priority queue</a>	Graph with  V  vertices and  E  edges	$O( V ^2)$	$O( V ^2)$	$O( V )$
<a href="#">Shortest path by Bellman-Ford</a>	Graph with  V  vertices and  E  edges	$O( V   E )$	$O( V   E )$	$O( V )$

## Sorting

Algorithm	Data Structure	Time Complexity			Worst Case Auxiliary Space Complexity
		Best	Average	Worst	Worst
<a href="#">Quicksort</a>	Array	$O(n \log(n))$	$O(n \log(n))$	$O(n^2)$	$O(n)$
<a href="#">Mergesort</a>	Array	$O(n \log(n))$	$O(n \log(n))$	$O(n \log(n))$	$O(n)$
<a href="#">Heapsort</a>	Array	$O(n \log(n))$	$O(n \log(n))$	$O(n \log(n))$	$O(1)$
<a href="#">Bubble Sort</a>	Array	$O(n)$	$O(n^2)$	$O(n^2)$	$O(1)$
<a href="#">Insertion Sort</a>	Array	$O(n)$	$O(n^2)$	$O(n^2)$	$O(1)$
<a href="#">Select Sort</a>	Array	$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(1)$
<a href="#">Bucket Sort</a>	Array	$O(n+k)$	$O(n+k)$	$O(n^2)$	$O(nk)$
<a href="#">Radix Sort</a>	Array	$O(nk)$	$O(nk)$	$O(nk)$	$O(n+k)$

## Data Structures

Data Structure	Time Complexity								Space Complexity Worst
	Average				Worst				
	Indexing	Search	Insertion	Deletion	Indexing	Search	Insertion	Deletion	
<a href="#">Basic Array</a>	$O(1)$	$O(n)$	-	-	$O(1)$	$O(n)$	-	-	$O(n)$
<a href="#">Dynamic Array</a>	$O(1)$	$O(n)$	$O(n)$	$O(n)$	$O(1)$	$O(n)$	$O(n)$	$O(n)$	$O(n)$
<a href="#">Singly-Linked List</a>	$O(n)$	$O(n)$	$O(1)$	$O(1)$	$O(n)$	$O(n)$	$O(1)$	$O(1)$	$O(n)$
<a href="#">Doubly-Linked List</a>	$O(n)$	$O(n)$	$O(1)$	$O(1)$	$O(n)$	$O(n)$	$O(1)$	$O(1)$	$O(n)$
<a href="#">Skip List</a>	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(n)$	$O(n)$	$O(n)$	$O(n)$	$O(n \log(n))$
<a href="#">Hash Table</a>	-	$O(1)$	$O(1)$	$O(1)$	-	$O(n)$	$O(n)$	$O(n)$	$O(n)$
<a href="#">Binary Search Tree</a>	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(n)$	$O(n)$	$O(n)$	$O(n)$	$O(n)$
<a href="#">Cartesian Tree</a>	-	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	-	$O(n)$	$O(n)$	$O(n)$	$O(n)$
<a href="#">B-Tree</a>	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(n)$
<a href="#">Red-Black Tree</a>	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(n)$
<a href="#">Splay Tree</a>	-	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	-	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(n)$
<a href="#">AVL Tree</a>	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(n)$

## Heaps

Heaps	Time Complexity						
	Heapify	Find Max	Extract Max	Increase Key	Insert	Delete	Merge
<a href="#">Linked List (sorted)</a>	-	$O(1)$	$O(1)$	$O(n)$	$O(n)$	$O(1)$	$O(m+n)$
<a href="#">Linked List (unsorted)</a>	-	$O(n)$	$O(n)$	$O(1)$	$O(1)$	$O(1)$	$O(1)$
<a href="#">Binary Heap</a>	$O(n)$	$O(1)$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(m+n)$
<a href="#">Binomial Heap</a>	-	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$	$O(\log(n))$

[Fibonacci Heap](#)-  $O(1)$   $O(\log(n))^*$   $O(1)^*$   $O(1)$   $O(\log(n))^*$   $O(1)$ 

## Graphs

Node / Edge Management	Storage	Add Vertex	Add Edge	Remove Vertex	Remove Edge	Query
<a href="#">Adjacency list</a>	$O( V  +  E )$	$O(1)$	$O(1)$	$O( V  +  E )$	$O( E )$	$O( V )$
<a href="#">Incidence list</a>	$O( V  +  E )$	$O(1)$	$O(1)$	$O( E )$	$O( E )$	$O( E )$
<a href="#">Adjacency matrix</a>	$O( V ^2)$	$O( V ^2)$	$O(1)$	$O( V ^2)$	$O(1)$	$O(1)$
<a href="#">Incidence matrix</a>	$O( V  \cdot  E )$	$O( V  \cdot  E )$	$O( V  \cdot  E )$	$O( V  \cdot  E )$	$O( V  \cdot  E )$	$O( E )$

## Notation for asymptotic growth

letter	bound	growth
(theta) $\Theta$	upper and lower, tight <sup>[1]</sup>	equal <sup>[2]</sup>
(big-oh) $O$	upper, tightness unknown	less than or equal <sup>[3]</sup>
(small-oh) $o$	upper, not tight	less than
(big omega) $\Omega$	lower, tightness unknown	greater than or equal
(small omega) $\omega$	lower, not tight	greater than

[1] Big O is the upper bound, while Omega is the lower bound. Theta requires both Big O and Omega, so that's why it's referred to as a tight bound (it must be both the upper and lower bound). For example, an algorithm taking Omega( $n \log n$ ) takes at least  $n \log n$  time but has no upper limit. An algorithm taking Theta( $n \log n$ ) is far preferential since it takes AT LEAST  $n \log n$  (Omega  $n \log n$ ) and NO MORE THAN  $n \log n$  (Big O  $n \log n$ ).<sup>SO</sup>

[2]  $f(x) = \Theta(g(n))$  means  $f$  (the running time of the algorithm) grows exactly like  $g$  when  $n$  (input size) gets larger. In other words, the growth rate of  $f(x)$  is asymptotically proportional to  $g(n)$ .

[3] Same thing. Here the growth rate is no faster than  $g(n)$ . big-oh is the most useful because represents the worst-case behavior.

In short, if algorithm is \_\_\_ then its performance is \_\_\_

### algorithm performance

$$o(n) < n$$

$$O(n) \leq n$$

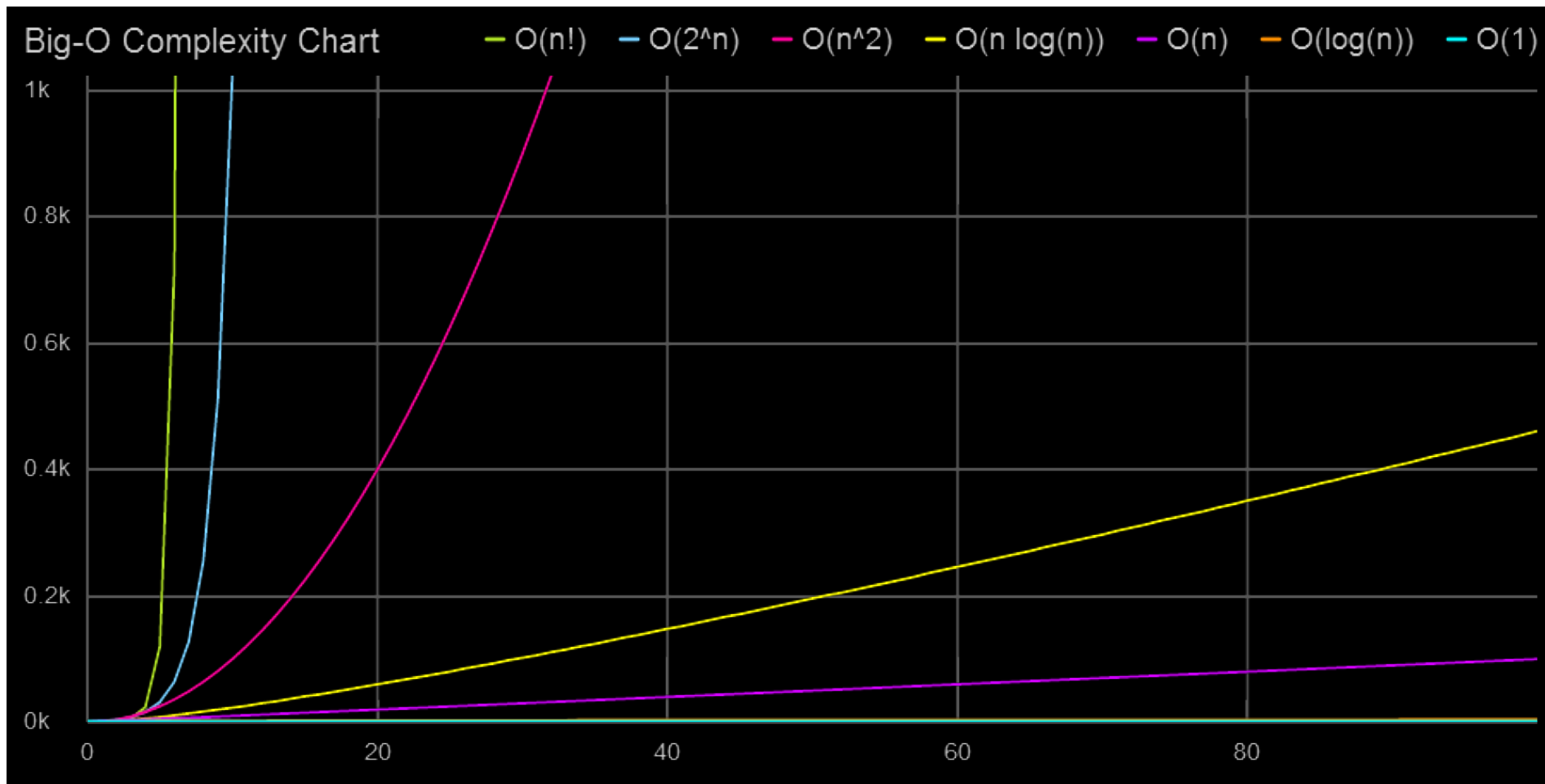
$$\Theta(n) = n$$

$$\Omega(n) \geq n$$

$$\omega(n) > n$$

## Big-O Complexity Chart

This interactive chart, created by our friends over at [MeteorCharts](#), shows the number of operations (y axis) required to obtain a result as the number of elements (x axis) increase.  $O(n!)$  is the worst complexity which requires 720 operations for just 6 elements, while  $O(1)$  is the best complexity, which only requires a constant number of operations for any number of elements.



## Contributors

[Edit these tables!](#)

1. [Eric Rowell](#)
2. [Quentin Pleple](#)
3. [Nick Dizazzo](#)
4. [Michael Abed](#)