
Critique Sorting Algorithms and Big-O Analysis

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Abstract

1 This report investigates and surveys a list of sorting algorithms and
2 discusses how sorting algorithms can affect the performance of soft-
3 ware production. The analysis focuses on comparison of different
4 sorting algorithms and their time space analysis using big-O notation.

5 1 Introduction of Algorithms

6 This section introduces some famous algorithms in computer science and computer
7 programming. Specifically, the paragraphs investigates the procedure of how these
8 algorithms can be implemented to maximize computation power such as processor per-
9 formance, data retrieval, processing, storage and distribution, and complex calculations
10 management.

11 Why sorting? Sorting is a fundamental programming technique. It is a computational and
12 mathematical process to rearrange a list of certain objects in a predefined order. Usually
13 the orders are ascending or descending according to certain numerical value. Many
14 literature have contributed to the survey of sorting algorithm (Estivill-Castro and Wood,
15 1992; Karunanithi et al., 2014; Martin, 1971; Zutshi and Goswami, 2021). Sorting
16 algorithm provides crucial component of algorithmic solutions in today's software
17 computing. It is also imperative to have consistent computing performance and the
18 development sorting algorithms increases the level of elegance of computing software
19 solutions. Throughout the years, the sorting algorithms have been developed by many
20 scholars and sometimes even similar ones have drastically different performance Zutshi
21 and Goswami (2021).

22 To assess the performance of sorting algorithm, two common perspectives are discussed.
23 They are time and space analysis. The time analysis refers to the time consumption
24 of a certain algorithm while the space analysis refers to the memory consumption of a
25 certain algorithm. As the definition suggests, it is desirable for computer scientists and
26 programmers to prefer algorithms that are fast but also consumes very little memory if
27 those algorithms are viable choices. There are Big-O and Omega to represent the time
28 complexity Zutshi and Goswami (2021). However, in this report, we focus on the Big-O
29 analysis. This report will examine a list of different sorting algorithms and their time
30 and space analysis will also be discussed in order to make sound comparisons Singh
31 et al. (2018); Martin (1971); Yu and Li (2022); Vitanyi (2007).

32 These enhancements of sorting algorithms provide fundamental building blocks to
33 mitigate the risks in a large-scale programming project, which is extremely important
34 for today's development of complicated tools in Artificial Intelligence.

35 **2 Why It Works**

36 This section discusses why the sorting algorithms such as bubble sort, quick sort, and
37 insertion sort work the way they do.

38 Almost all sorting algorithms are recursive. This means that there is some sort of
39 for loop in the algorithm and the lists and sub-lists keep increasing or decreasing in
40 certain direction and sometimes according to certain thresholds. This is accomplished
41 in a way to correct a target's value according to the algorithm. The beauty of these
42 algorithms falls on the nature that a certain action (such as swap or change of order) is
43 carried on when certain thresholds trigger the action. Many dynamic algorithms can be
44 designed when nested for loops are used. To check certain sub-lists of the information,
45 the algorithm traverses through the list according to certain direction and predefined
46 comparisons are evaluated before an action is called.

47 In addition to the design that enables the algorithms to run continuously, another key
48 component to allow sorting algorithms to work well is that eventually it stops. Every
49 sorting algorithms must have a stopping rule. Otherwise there can be an infinite loop
50 created. There cannot be an infinite loop in the code or the program will run a long
51 time until eventually it exhausts all the available memory and crashes. Stopping rule is
52 the second important thing in algorithmic design. A good stopping rule (or sometimes
53 dropping rule) can increase the efficiency of an algorithm drastically.

54 **3 Different Sorting Algorithms**

55 This section provides discussion of a list of famous algorithms in sorting techniques.
56 They include bubble sorts, quick sorts, and insertion sorts. We discuss of they can
57 effectively be used as support to increase production value and computational efficiency
58 of large-scale programming.

59 The first candidate is Bubble Sort which is the most fundamental sorting algorithm to
60 introduce in the field. The Bubble Sort also has a nickname called Sinking Sort. The
61 algorithm in this strategy compares the two numbers adjacent together throughout the
62 list and changes their order if they are incorrect. This change of order continues until
63 the repetition ends when all the numbers are compared and sorted. For example, the
64 goal is to sort the list {5, 1, 4, 2}. The algorithm starts by comparing 5 with 1. Since 5
65 is greater than 1, the order of these two numbers is changed. Then we have {1, 5, 4, 2}.
66 Then the algorithm arrives at the number 5 and compares 5 with the next number which
67 is 4. Since 5 is greater than 4, then the algorithm changes the order between 5 and 4.
68 Hence, a new list {1, 4, 5, 2} is generated. The last pair is 5 and 2, so 2 gets put in front
69 of the number 5 because the numerical value is smaller. Hence, we have {1, 4, 2, 5} for
70 one pass. One pass refers to one round from the first number to the last number. After
71 the first pass, some numbers are sorted correctly, however, some are incorrect still. The
72 algorithm does a second pass. The second pass continues to 4 and 2. Then the algorithm
73 swaps their order to obtain {1, 2, 4, 5}. The algorithm continues to check and change
74 the order if necessary. The algorithm stops in the next round, because there is nothing
75 that needs to be changed and the algorithm finishes. A sample code, in Python, can be
76 seen below to demonstrate this technique.

```

77
78 # Python program for implementation of Bubble Sort
79 def bubble_sort(some_array):
80     n = len(some_array)
81
82     # Traverse through all array elements
83     for i in range(n):
84
85         # Last i elements are already in place
86         for j in range(0, n-i-1):
87
88             # traverse the array from 0 to n-i-1
89             # Swap if the element found is greater
90             # than the next element
91             if some_array[j] > some_array[j+1]:
92                 some_array[j], some_array[j+1] = some_array[j+1],
93                 ↪ some_array[j]

```

95 Since the algorithm of Bubble Sort checks every pair and it can result in an exploding
96 number of different passes, it is generally not a go-to choice for programmers. This is
97 because the worst-case performance is $\mathcal{O}(n^2)$ comparisons and $\mathcal{O}(n^2)$. Though the best-
98 case scenario the code can finish within $\mathcal{O}(n)$ comparisons and $\mathcal{O}(1)$ swaps. Sometimes,
99 at extreme case, the time complexity can be $\mathcal{O}(n \log n)$ which is extremely slow value.

100 The next algorithm to be introduced is called Quick Sort. This type of algorithm is an
101 in-place sorting technique. Originally, it was created by a British computer scientist in
102 1959. His name is Tony Hoare and he published this work in 1961. This type of sorting
103 algorithm is still very common and received a lot of credibility in the field of computer
104 science. Due to its design, it earns a nickname called “divide and conquer”. This is
105 because the algorithm select pivot element and sort in between sub-arrays. Sometimes
106 the process can be considered partition-exchange sort. The worst-case scenario there
107 needs to be $\mathcal{O}(n^2)$ where the best-case scenario it is $\mathcal{O}(n \log n)$. A sample python code
108 that executes Quick Sort is presented below.

```

109
110 # This area is for the python script. In this script, the code
111     ↪ implements a quick sort algorithm. The algorithm has a
112     ↪ helper function and a main function.
113
114 # start here:
115 def helper(some_array, low_value, high_value):
116
117     # choose the value on the right
118     pivot_value = some_array[high_value]
119
120     # redefine the running index i
121     i = low_value - 1
122
123     # traverse the list and evaluate all elements
124     # make comparisons of the item selected with the pivot_value
125     for j in range(low_value, high_value):
126         if some_array[j] <= pivot_value:
127             # if the item triggers the condition,
128             # change the order and then redefine i
129             i = i + 1
130
131     # change order or replace i with element at j

```

```

132     (some_array[i], some_array[j]) = (some_array[j], some_array[
133         ↪ i])
134
135     # change or update pivot_value value
136     (some_array[i + 1], some_array[high_value]) = (some_array[
137         ↪ high_value], some_array[i + 1])
138
139     # output
140     return i + 1
141
142 # Function to perform quicksort
143 def quick_sort(some_array, low_value, high_value):
144     if low_value < high_value:
145
146         # Find pivot element such that
147         # element smaller than pivot are on the left
148         # element greater than pivot are on the right
149         pi = helper(some_array, low_value, high_value)
150
151         # Recursive call on the left of pivot
152         quick_sort(some_array, low_value, pi - 1)
153
154         # Recursive call on the right of pivot
155         quick_sort(some_array, pi + 1, high_value)

```

157 The third candidate is called Insertion Sort. As the name suggests, this type of sorting
158 algorithm takes an element from a list of an array of numbers and insert it inside a
159 previous subset of array. In other words, the algorithm starts with a random array of
160 numbers that is unsorted and then takes one element one by one to compare with the
161 previous subset. For example, consider an list of numbers {5, 1, 4, 2}. The algorithm
162 starts with number 5 and since there is only one number then nothing changes. Then this
163 number 5 forms a sub-list for comparisons. Then the algorithm moves on to the next
164 number which is 1. Since 1 is less than 5, the algorithm puts 1 on the left side of 5. As of
165 this step, the list becomes {1, 5, 4, 2}. The algorithm continues and reads 4. The number
166 4 is less than 5, so it gets to be moved in front of 5. Then the algorithm compares 1
167 and 4. Since 4 is greater than 1, there is no need to make any additional changes. Now
168 the list becomes {1, 4, 5, 2}. The last number that has yet to be reorganized is 2. The
169 algorithm reads 2 and iteratively compare the number 2 with the previous sub-list from
170 large to small. Hence, the number 2 gets placed in between 1 and 4. Thus, we have a
171 sorted list {1, 2, 4, 5}. An example of code, written in python, is presented below.

```

172
173 # This area is for python script. The code presents a function for
174     ↪ insertion sort algorithms.
175
176 # start here:
177 def insertion_sort(some_array):
178
179     # Traverse through 1 to len(some_array)
180     for i in range(1, len(some_array)):
181
182         key = some_array[i]
183
184         # Move elements of some_array[0..i-1], that are
185         # greater than key, to one position ahead
186         # of their current position

```

```

187     j = i-1
188     while j >= 0 and key < some_array[j] :
189         some_array[j + 1] = some_array[j]
190         j -= 1
191     some_array[j + 1] = key

```

193 For Insertion Sort, the worst-case performance is the same as above which is $\mathcal{O}(n^2)$ for
194 both comparisons and change of orders. The best-case is also the same which is $\mathcal{O}(n)$
195 for comparisons and $\mathcal{O}(1)$ for change of order.

196 4 Big-O Analysis

197 This section discusses the Big-O notation and provides a high-level overview of how it
198 works in a search-based algorithm. There are different levels of time space complexity.
199 There are also an overview of Big-O notation.

200 First, let us introduce some definitions. The Big-O notation measures the efficiency
201 of a designed algorithm. This mathematical expression evaluates the speed and time
202 consumption of the algorithm depends on the length of the data. It is a commonly
203 used notation to quickly indicate the complexity of a data structure and algorithmic
204 design. The function is famous at measuring two efficiencies. They are time and space.
205 Both time and space are important performance measure metrics to allow computer
206 programmers to understand how “good” the algorithm is Devi et al. (2011); Emmanuel
207 et al. (2021); Ghent (2020).

208 The Big-O notation can also be referred to as the upper bound of a certain algorithm.
209 The upper bound of some time consumption function based on the length of the search
210 is considered as the worst-case scenario. It is indeed the worst-case scenario that is
211 informative, because programmers cannot hope to see best-case scenario all the time.
212 That would be a dangerous assumption to make in production. To truly understand
213 how Big-O notation works in a search algorithm, it is easy to demonstrate it with the
214 following example. Consider a search algorithm that tries to find the number 8 from a
215 list of arrays 1 to 8. A simple one is to look for each item one by one. The algorithm
216 starts with the first number. If it is not 8, then the algorithm continues to 2. It continues
217 the search until the algorithm finds the number 8 in the list. A sample code can be seen
218 below.

```

219 def linear_search(some_array, some_number):
220     for i in range(len(some_array)):
221         if some_array[i] == some_number:
222             return i
223     return -1 # while -1 is commonly representing error code or
224             ↪ desired result not found
225

```

227 Though the linear search is straightforward and it makes perfect sense, it may not be the
228 most efficient search possible. Another potential way is the binary search. Before we
229 introduce binary search, a simple mathematical concept is important to be of aid here.
230 It is called mean value theorem. The theorem states the following. When a function
231 h is continuous on the closed interval $[z_1, z_2]$ and differentiable on the open interval
232 (z_1, z_2) , then there exists a point z_3 in the interval (z_1, z_2) such that the derivative of the
233 function $h'(z_3)$ is equal to the function’s average rate of change over $[z_1, z_2]$. Here we
234 assume that the numbers z_1, z_2, z_3 are in real line, i.e. $\forall i \in [1, 2, 3], z_i \in \mathbb{R}$. The proof
235 is essentially a two step process. It cuts from the middle and then it makes a comparison.

236 The idea can be applied here as well in binary sort. In other words, to take the idea and
 237 apply it in search algorithm, the algorithm suggests to take a middle point between 1
 238 to 8. We can take 4 as the middle point. Since 4 is less than 8, that means the number
 239 8 must be on the right half of the sub-list. This means there is no purpose of checking
 240 the left half of the sub-list and so we omit the left half. For the right remaining half, the
 241 algorithm cut it in half again and this time we can use 6 as mid-point. Since 6 is less
 242 than 8, that means we can drop 5 and 6. This means we only have 7 and 8 left. The
 243 same algorithm continues until we find where 8 is. In this case, the binary search is
 244 more efficient, because it eliminates half of the list in each search round. The worst case
 245 scenario for binary search is $\mathcal{O}(\log N)$. A sample code is represented below

```

246 def binary_search(some_array, some_target):
247     left = 0
248     right = len(some_array) - 1
249
250
251     while left <= right:
252         midpoint = (left + right) // 2
253         if some_target < some_array[midpoint]:
254             right = midpoint - 1
255         elif some_target > some_array[midpoint]:
256             left = midpoint + 1
257         else:
258             return midpoint
259     return -1 # while -1 is commonly representing error code or
260             ↪ desired result not found
261
  
```

262 4.1 Time Analysis

263 This section discuss how Big-O analysis supports processing times for each sorting algo-
 264 rithm. Further, it discuss Big-O alternatives to the management of complex algorithms.
 265 Support your discussion with scholarly literature.

266 The Big-O notation, as demonstrated in earlier paragraphs of this section, can be simpli-
 267 fied to manage complex algorithms. In other words, for binary search we use $\mathcal{O}(\log N)$
 268 which is less complex than linear search. Many other algorithms that are more compli-
 269 cated can also exist as well and we use Big-O to analyze their level of complexities. A
 270 common example can be the quadratic algorithm which takes $\mathcal{O}(N^2)$. The algorithm
 271 has nested loops and it suggests to iterate through the entire data in an outer loop. A list
 272 of complexities is presented in Table 1.

Table 1: List of Different Level of Complexities

Factorial	Exponential	Cubic	Quadratic	$N \times \log N$	Linear	Logarithmic	Constant
$\mathcal{O}(N!)$	$\mathcal{O}(2^N)$	$\mathcal{O}(N^3)$	$\mathcal{O}(N^2)$	$\mathcal{O}(N \log N)$	$\mathcal{O}(N)$	$\mathcal{O}(\log N)$	$\mathcal{O}(1)$

273 The level of complexity accompanying with the efficiency of speed is presented in the
 274 Figure 1 and a more detailed graph is in Figure 2.

275 A more detailed graph can be seen

276 References

277 Devi, S. G., Selvam, K., and Rajagopalan, S. (2011). An abstract to calculate big o
 278 factors of time and space complexity of machine code.

Figure 1: Summary of Big-O Complexity Chart

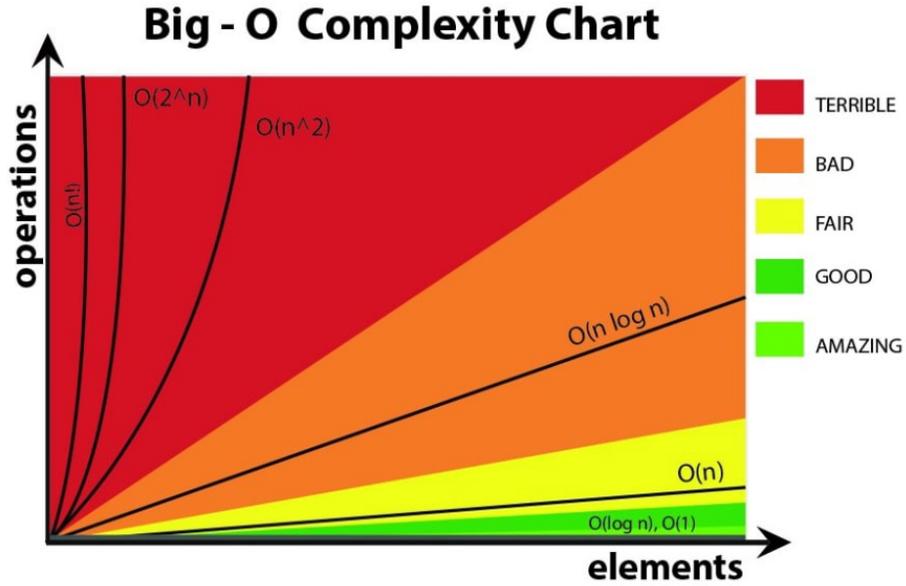


Figure 2: Summary of Big-O Complexity Chart (Detailed)

<BIG-O-CHEATSHEET>
www.bigochatsheet.com

DATA STRUCTURE Operations

DATA Structure	Average				Worst				Worst
	Access	Search	Insertion	Deletion	Access	Search	Insertion	Deletion	
Array	$O(1)$	$O(e)$	$O(e)$	$O(e)$	$O(1)$	$O(e)$	$O(e)$	$O(e)$	$O(e)$
Stack	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$
Queue	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$
Empty-Linked List	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$
Doubly-Linked List	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$	$O(e)$	$O(1)$	$O(1)$	$O(e)$
Heap List	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(n)$	$O(n)$	$O(e)$	$O(n)$	$O(n \log n)$
Hash Table	N/A	$O(1)$	$O(1)$	$O(1)$	N/A	$O(e)$	$O(e)$	$O(e)$	$O(e)$
Binary Search Tree	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(n)$	$O(n)$	$O(e)$	$O(n)$	$O(n)$
Carson Tree	N/A	$O(\log n)$	$O(\log n)$	$O(\log n)$	N/A	$O(e)$	$O(e)$	$O(e)$	$O(e)$
B-Tree	$O(\log n)$	$O(n)$							
Red-Black Tree	$O(\log n)$	$O(n)$							
Splay Tree	N/A	$O(\log n)$	$O(\log n)$	$O(\log n)$	N/A	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(n)$
AVL Tree	$O(\log n)$	$O(n)$							
B+ Tree	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(\log n)$	$O(n)$	$O(n)$	$O(e)$	$O(n)$	$O(n)$

ARRAY SORTING Algorithms

ARRAY Algorithms	Best	Average	Worst	Worst
	TIME Complexity	TIME Complexity	TIME Complexity	SPACE Complexity
QuickSort	$O(n \log n)$	$O(n \log n)$	$O(n^2)$	$O(\log n)$
MergeSort	$O(n \log n)$	$O(n \log n)$	$O(n \log n)$	$O(n)$
TimSort	$O(n)$	$O(n \log n)$	$O(n \log n)$	$O(1)$
HeapSort	$O(n \log n)$	$O(n \log n)$	$O(n \log n)$	$O(1)$
Bubble Sort	$O(n)$	$O(n^2)$	$O(n^2)$	$O(1)$
Insertion Sort	$O(n)$	$O(n^2)$	$O(n^2)$	$O(1)$
Selection Sort	$O(n^2)$	$O(n^2)$	$O(n^2)$	$O(1)$
Tree Sort	$O(n \log n)$	$O(n \log n)$	$O(n^2)$	$O(n)$
Shell Sort	$O(n \log n)$	$O(n \log n)^2$	$O(n^2)$	$O(1)$
Bucket Sort	$O(n+k)$	$O(n+k)$	$O(n^2)$	$O(n)$
Radix Sort	$O(nk)$	$O(nk)$	$O(nk)$	$O(n+k)$
Counting Sort	$O(n+k)$	$O(n+k)$	$O(n+k)$	$O(n)$
Cocktail	$O(n)$	$O(n \log n)$	$O(n \log n)$	$O(n)$

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