In computer science, big O notation is used to classify algorithms by how they respond (e.g., in their processing time or working space requirements) to changes in input size.

#### For a general example that is understandable:

Pick a number between 1 and 1000. I guess 500. You say "higher". I guess 750. You say "lower." I choose 625... Clearly my search is not going to take 1000 guesses (order n). I chop my search domain in half each time and take 10 guesses or less

"If I have n items and each time through the loop I can throw out half of them, how many times do I have to go through the loop until there's only one remaining?" This is the analysis for binary sort. If I've gone through the loop k times, then I have  $1/2^k$  items remaining. So I want to find k such that  $n/2^k = 1$ . This is the same as  $n=2^k$  or  $k = \log_2 n$ .

### **Beginners Guide:**

Big O notation is used in Computer Science to describe the performance or complexity of an algorithm. Big O specifically describes the worst-case scenario, and can be used to describe the execution time required or the space used (e.g. in memory or on disk) by an algorithm.

### O(1)

O(1) describes an algorithm that will always execute in the same time (or space) regardless of the size of the input data set.



### O(N)

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O(N) describes an algorithm whose performance will grow linearly and in direct proportion to the size of the input data set. The example below also demonstrates how Big O favors the worst-case performance scenario; a matching string could be found during any iteration of the for loop and the function would return early, but Big O notation will always assume the upper limit where the algorithm will perform the maximum number of iterations.

bool ContainsValue(String[] strings, String value)

for(int i = 0; i < strings.Length; i++) {

```
if(strings[i] == value)
{
return true;
}
}
return false;
```

### O(N<sup>2</sup>)

}

 $O(N^2)$  represents an algorithm whose performance is directly proportional to the square of the size of the input data set. This is common with algorithms that involve nested iterations over the data set. Deeper nested iterations will result in  $O(N^3)$ ,  $O(N^4)$  etc.



 $O(2^{N})$  denotes an algorithm whose growth will double with each additional element in the input data set. The execution time of an  $O(2^{N})$  function will quickly become very large.

### Logarithms

Logarithms are slightly trickier to explain so I'll use a common example:

Binary search is a technique used to search sorted data sets. It works by selecting the middle element of the data set, essentially the median, and compares it against a target value. If the values match it will return success. If the target value is higher than the value of the probe element it will take the upper half of the data set and perform the same operation against it. Likewise, if the target value is lower than the value of the probe element it will continue to halve the data set with each iteration until the value has been found or until it can no longer split the data set.

This type of algorithm is described as O(log N). The iterative halving of data sets described in the binary search example produces a growth curve that peaks at the beginning and slowly flattens out as the size of the data sets increase e.g. an input data set containing 10 items takes one second to complete, a data set containing 100 items takes two seconds, and a data set containing 1000 items will take three seconds. Doubling the size of the input data set has little effect on its growth as after a single iteration of the algorithm the data set will be halved and therefore on a par with an input data set half the size. This makes algorithms like binary search extremely efficient when dealing with large data sets.

**Computational Complexity:** It is very interesting and useful as it helps a programmer to find out the the complexity of a set of possible algorithms for a particular programming task, thus helping him to select the algorithm with minimum complexity in terms of number of instructions involved. So here we will explain what is Computational Complexity, Big O notation to compare algorithms and analysis of the most popular searching and sorting methods.

What is an algorithm: An algorithm is a sequence of instructions that act on some input data to produce some output in a finite number of steps.

Why analyze algorithm: Determining which algorithm is efficient than the other involves analysis of algorithms.

Factors considered in analysis: Two factors considered while analyzing algorithms are time and space.

- **Time:** Actual run time on a particular computer is not a good basis for comparison since it depends heavily on the speed of the computer, the total amount of RAM, the Operating System running on the system and the quality of the computer used. So the complexity of an algorithm is the number of elementary instructions performed with respect to the size of the input data.
- **Space:** This is a less important factor than time because if more space is required, it can always be found in the form of auxiliary storage.

**What is Computational Complexity:** It refers to the measure of the performance of an algorithm. It allows the comparison of algorithm for efficiency and predicts their behavior as data size increases.

**Dominant Term:** While describing the growth rate of an algorithm, we simply consider the term which affects the most on the algorithm's performance. This term is known as the dominant term.

#### Example:

//to count no. of characters in a file

count=0

While(there are more characters in a file) do

increment count by 1

get the next character

End While

Print count

In the above example, no of various instructions for a file size of 500 characters,

Initialization: 1 instruction

Increments: 500

Conditional checks: 500 + 1 (for eof)

Printing: 1

Initialization and Printing is same for any size of file so they are insignificant compared to increments and checks. So increments and checks are the dominant terms in the above example.

**Best, Average and Worst Case Complexity:** In most algorithms, the actual complexity for a particular input can vary. E.g. If input list is sorted, linear search may perform poorly while binary search will perform very well. Hence, multiple input sets must be considered while analyzing an algorithm. These include the following

- Best Case Input: This represents the input set that allows an algorithm to perform most quickly. With this input, the algorithm takes the shortest time to execute, as it causes the algorithms to do the least amount of work. It provides the way an algorithm behaves under optimal conditions. E.g. In a searching algorithm, if match is found at the first location, it is the best case input as the no. comparisons is just one.
- 2. Worst Case Input: This represents the input set that allows an algorithm to perform most slowly. It is an important analysis because it gives us an idea of the maximum time an algorithm will ever take. It is important because it provides an upper bound on running time of an algorithm. And it is also a promise that the algorithm will not take more than the calculated time. Eg. In a searching algorithm, if value to be searched is at the last location or it is not in the list, is the worst case input because it tells the maximum number of comparisons that have to be made.

3. Average Case Input: This represents the input set that allows an algorithm to deliver an average performance. It provides the expected running time. It needs assumption of statistical distribution of inputs.

Rate of growth: The growth rate determines the algorithm's performance when the input size grows.

**Big O Notation:** The Big O Notation is a class of mathematical formula that best describes an algorithm's growth rate. It is very useful:

- 1. For comparing the performance of two or more algorithms.
- 2. It frees us from bothering about constants.

Let f(n), g(n) be two functions. Then, f(n) is O(g(n)) if there exists constants a, b such that :

 $F(n) \le a * g(n)$  whenever  $n \ge b$ 

E.g. If,  $f(n) = n^2 + 100n$ 

and,  $g(n) = n^2$ , and a=2 , and b=100

then, f(n) is O(g(n))

Because  $(n^2 + 100n)$  is less than or equal to  $(2n^2)$  for all n greater than or equal to 100.

It means that eventually for  $n \ge b$ , f(n) becomes permanently smaller or equal to some multiple of g(n).

In other words, f(n) is a smaller function than g(n) or f(n) is asymptotically bounded by g(n) or f(n) grows slower than g(n) or g(n) does not better than f(n) in solving the problem.

#### **Common Growth Rates**

Algorithm	Time Complexity	
Linear Search	O(n) – Worst & Average Case	
	O(1) – Best case	
Binary Search	O(log <sub>2</sub> n)-Worst &Average Case	
	O(1) - Best Case	
Bubble Sort	O(n <sup>2</sup> )- All cases	
Selection Sort	O(n <sup>2</sup> ) – All cases	
Quick Sort	O(n <sup>2</sup> ) – Worst case	
(fastest because of its low overhead and average O(n log n) behavior)	O(n log n) - Average and best Case	

Merge Sort	O(n log n) – in all cases
(needs additional space for auxiliary array and twice as assignments as Quick Sort on the average)	s many
Insertion Sort	O(n <sup>2</sup> ) – Worst & Average Case
	O(n) – Best Case
Binary Tree Sort ( i.e. Creation of Binary search tree)	O(n <sup>2</sup> ) – Worst case
	O(n log n) – Average & Best Case
Simultaneous Linear Equations	O(n <sup>3</sup> )
Adding a node to the front of a linked list	O(1)
Towers of Hanoi	O(2 <sup>n</sup> )
//value to be searched is item Begin EOR L = 0.TO $(n-1)$ BY 1.DO	
IF ( a[i] = item) THEN SET loc = i	
ENDIF	
ENDFOR SET loc = -1	
END	

**Worst Case**: Worst case is achieved with an unsuccessful search which takes n comparisons. So worst case running time complexity is O(N).

Average case: Assuming the element would be found in the middle of the list or N/2, Average case complexity is also O(N) since it is divided by constant factor 2.

**Best Case:** Element is found at first index. Since only one comparison is made, it gives a constant time complexity of O(1).

#### 2. Binary Search:

//Array size is arr[n] BEGIN SET Low=0 SET high= n-1 WHILE (low<=high) DO SET Mid = (low+high)/2 IF(key = arr[md]) THEN SET Pos=mid ELSE IF (key < arr[mid]) THEN SET High = mid -1 ELSE SET Low = mid+1 ENDIF ENDIF ENDWHILE END

### Worst Case and Average Case Complexity.

Each comparison in the binary search reduces the number of possible candidates by a factor of 2. Thus the maximum no. of key comparisons is  $2 * \log_2 n$  (as two comparisons are made each time ie. K = arr[mid] and key<arr[mid])

 $= O(\log_2 n) = O(\log n)$ 

#### Best Case Complexity.

= O(1)

#### Linear Search Vs Binary Search:

- 1. Linear Search compares the value with each data item in the list sequentially whereas Binary search repeatedly divides the array in two halves and compares the value with the data item at mid value.
- 2. Average case complexity of Linear search is O(n) whereas of binary search is  $O(\log_2 n)$ .
- 3. The benefit of Binary search over Linear search becomes significant for lists over about 100 elements.
- 4. For similar lists Linear search may be faster because of the speed of the simple increment compared with the divisions needed in Binary search.
- 5. For large lists, Binary search is very much faster than Linear search but is not good for small lists.
- 6. Binary search is not good for linked lists structure as there is no random access for the middle term.

### 3. Bubble Sort:

BEGIN

//Array arr[] of size n
FOR i=0 TO n-1 BY 1 DO
FOR j=0 TO n-1 BY 1 DO
IF ( arr[j] > arr[j+1]) THEN
SET temp=arr[j]
SET arr[j]=arr[j+1]
SET arr[j+1]=temp
ENDIF
ENDFOR
ENDFOR
ENDFOR

### Best, Worst and Average Case Complexity:

No. of key comparisons:

= (n-1) \* (n-1) =  $n^2 - 2n + 1$ =  $O(n^2)$ 

Bubble Sort is simple and requires little additional space for interchanging i.e. one record to hold temporary value.

### 4. Insertion Sort:

BEGIN

//Array arr[] of size n

FOR j = 2 TO n BY 1 DO

SET key = arr[j]

SET i= j-1

WHILE i>0 AND arr[i]>key DO

SET arr[i+1]=arr[i]

ENDWHILE

SET i=i-1

ENDFOR

SET arr[i+1]=key

END

**Best case Complexity:** If list is sorted then only one comparison is made on each pass so, complexity is O(n)

Worst and Average Case Complexity: For unsorted list, no. of comparisons required are:

=( n\*(n-1))/2

 $= (n^2 - n)/2$ 

= O(n<sup>2</sup>)

5. Selection Sort:



END

### Best and Average Case Complexity:

Assuming file size n is a power of 2,

- 1. Divide and conquer technique divides each file in a subfile of size n/2; so total of l;og n times file is split.
- 2. Bringing pivot to its final position requires n comparisons.

So, Quick Sort is O(n log n).

### Worst Case Complexity:

Assuming file is sorted or nearly sorted, then taking the highest or the lowest element to the other side, splits file in a size of 0 and n-1. If the process repeats, a total of n-1 subfiles are sorted – the first of size n, the second of size n-1, third of size n-1 and so on.

Assuming K comparisons to rearrange a file, total comparisons required are

- =  $N + (n-1) + (n-2) + \dots + 2$  (because n-1 levels will be there)
- $= O(n^2)$

**7. Merge Sort:** Maximum passes in the merge sort method are log2 n; each pass involving n or fewer comparisons so merge sort is O(n log n).