

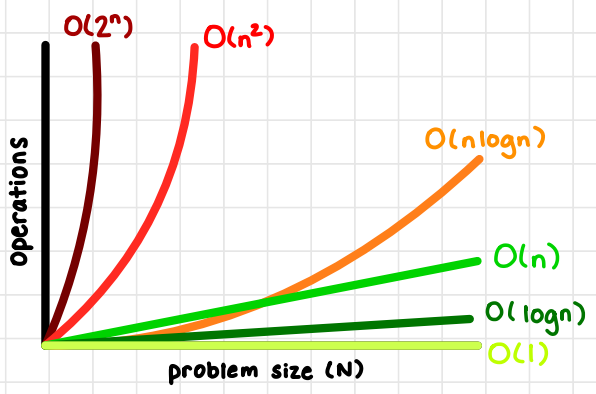


# time complexity

We evaluate an algorithm's performance by counting the number of operations relative to the problem size.

Sorting a list with 10,000 elements will take more time than sorting a list with 10 elements. The **Problem Size** would be the length of the list.

We usually use the variable N to denote problem size.



## big-O notation

"Big-O" refers to the upper bound of the relationship between the number of operations and the problem size. We are concerned with how large the function grows as N increases.

We only reference the dominant term of the function. For example -

$$5n^2 \text{ becomes } O(n^2)$$

$$5^n + 7n \text{ becomes } O(5^n)$$

**$O(1)$  Constant Time**  
 The algorithm completes within some constant, regardless of size.  
 e.g. getters/setters  
 type predicates  
 simple arithmetic

**$O(n)$  Linear Time**  
 The time for the algorithm to complete scales with the problem size.  
 e.g. traversing a list

**$O(\log n)$  Logarithmic Time**  
 The problem size is halved with each iteration.  
 e.g. binary search

**$O(2^n, 3^n)$  Exponential Time**  
 Increasing the problem size by 1 doubles the time.

**$O(n \log n)$**   
 e.g. QuickSort  
 Merge Sort

**$O(n^2), O(n^3) \dots$  Polynomial Time**  
 Usually an  $O(n)$  algorithm that performs an  $O(n)$  operation for N elements.