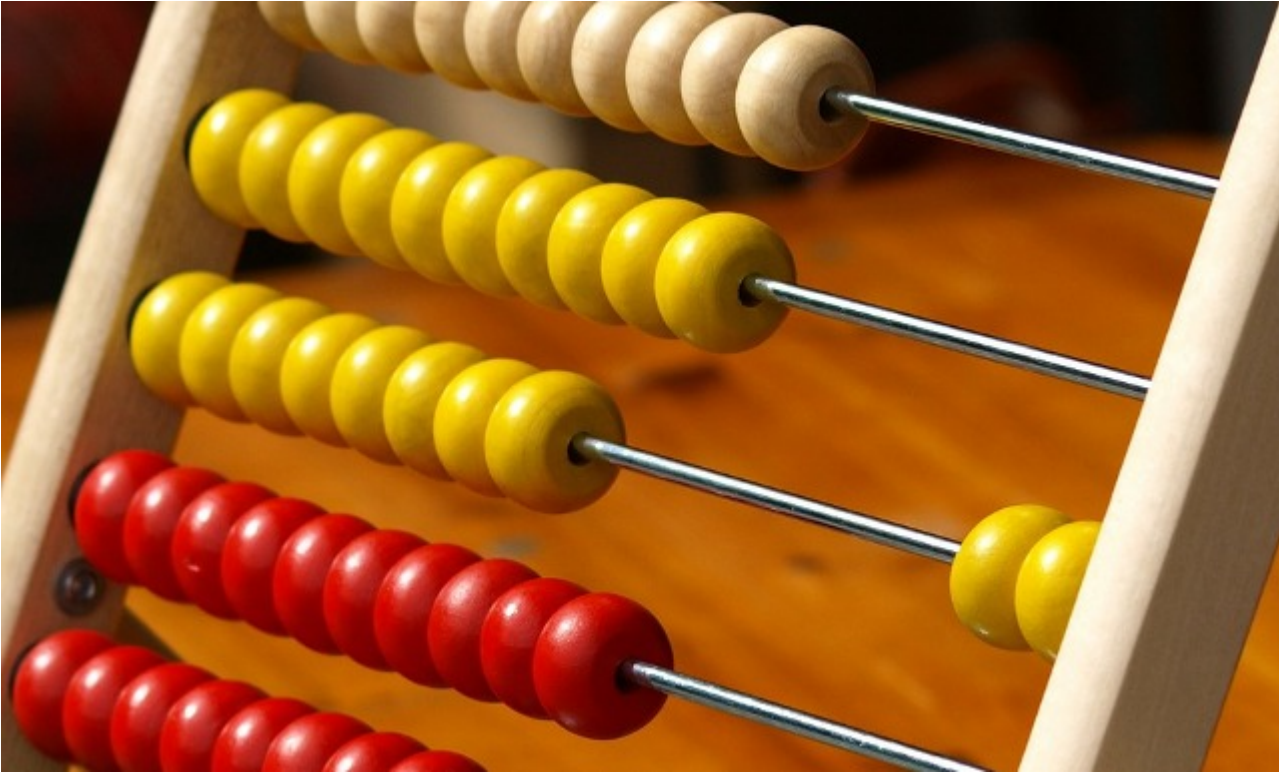


# How to analyze time complexity: Count your steps

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Time complexity estimates the time to run an algorithm. It's calculated by counting elementary operations.



Example (iterative algorithm)

Worst-case time complexity

Average-case time complexity

Quadratic time complexity

## Example (iterative algorithm)

What's the running time of the following algorithm?

```
// Compute the maximum element in the array a.  
Algorithm max(a):  
    max ← a[0]  
    for i = 1 to len(a)-1  
        if a[i] > max  
            max ← a[i]  
    return max
```

The answer depends on factors such as input, programming language and runtime, coding skill, compiler, operating system, and hardware.

We often want to reason about **execution time** in a way that depends only on the **algorithm** and its **input**. This can be achieved by choosing an **elementary operation**, which the algorithm performs repeatedly, and define the **time complexity**  $T(n)$  as the number of such operations the algorithm performs given an array of length  $n$ .

For the algorithm above we can choose the comparison  $a[i] > \max$  as an elementary operation.

1. This captures the running time of the algorithm well, since comparisons dominate all other operations in this particular algorithm.
2. Also, the time to perform a comparison is constant: it doesn't depend on the size of  $a$ .

The time complexity, measured in the number of comparisons, then becomes  $T(n) = n - 1$ .

In general, an **elementary operation** must have two properties:

1. There can't be any other operations that are performed more frequently as the size of the input grows.
2. The time to execute an elementary operation must be constant: it mustn't increase as the size of the input grows. This is known as **unit cost**.

## Worst-case time complexity

Consider this algorithm.

```
// Tell whether the array a contains x.  
Algorithm contains(a, x):  
    for i = 0 to len(a)-1  
        if x == a[i]  
            return true  
    return false
```

The comparison  $x == a[i]$  can be used as an elementary operation in this case. However, for this algorithm the number of comparisons depends not only on the number of elements,  $n$ , in the array but also on the value of  $x$  and the values in  $a$ :

- If  $x$  isn't found in  $a$  the algorithm makes  $n$  comparisons,
- but if  $x$  equals  $a[0]$  there is only one comparison.

Because of this, we often choose to study **worst-case** time complexity:

- Let  $T_1(n), T_2(n), \dots$  be the execution times for all possible inputs of size  $n$ .
- The worst-case time complexity  $W(n)$  is then defined as  $W(n) = \max(T_1(n), T_2(n), \dots)$ .

The worst-case time complexity for the contains algorithm thus becomes  $W(n) = n$ .

Worst-case time complexity gives an upper bound on time requirements and is often easy to compute. The drawback is that it's often overly pessimistic.

See [Time complexity of array/list operations](#) for a detailed look at the performance of basic array operations.

## Average-case time complexity

**Average-case** time complexity is a less common measure:

- Let  $T_1(n), T_2(n), \dots$  be the execution times for all possible inputs of size  $n$ , and let  $P_1(n), P_2(n), \dots$  be the probabilities of these inputs.
- The average-case time complexity is then defined as  $P_1(n)T_1(n) + P_2(n)T_2(n) + \dots$

Average-case time is often harder to compute, and it also requires knowledge of how the input is distributed.

## Quadratic time complexity

Finally, we'll look at an algorithm with poor time complexity.

```
// Reverse the order of the elements in the array a.  
Algorithm reverse(a):  
  for i = 1 to len(a)-1  
    x ← a[i]  
    for j = i downto 1  
      a[j] ← a[j-1]  
    a[0] ← x
```

We choose the assignment  $a[j] \leftarrow a[j-1]$  as elementary operation. Updating an element in an array is a constant-time operation, and the assignment dominates the cost of the algorithm.

The number of elementary operations is fully determined by the input size  $n$ . In fact, the outer for loop is executed  $n - 1$  times. The time complexity therefore becomes

$$W(n) = 1 + 2 + \dots + (n - 1) = n(n - 1)/2 = n^2/2 - n/2.$$

The quadratic term dominates for large  $n$ , and we therefore say that this algorithm has **quadratic** time complexity. This means that the algorithm **scales poorly** and can be used **only for small input**: to reverse the elements of an array with 10,000 elements, the algorithm will perform about 50,000,000 assignments.

In this case it's easy to find an algorithm with **linear** time complexity.

```
Algorithm reverse(a):  
  for i = 0 to n/2  
    swap a[i] and a[n-i-1]
```

This is a **huge improvement** over the previous algorithm: an array with 10,000 elements can now be reversed with only 5,000 swaps, i.e. 10,000 assignments. That's roughly a 5,000-fold speed improvement, and the improvement keeps growing as the the input gets larger.

It's common to use **Big O notation** when talking about time complexity. We could then say that the time complexity of the first algorithm is  $\Theta(n^2)$ , and that the improved algorithm has  $\Theta(n)$  time complexity.