

Algorithms and Algorithm Analysis

Algorithm: A clearly specified set of instructions the computer will follow to solve a problem.

Given an algorithm, we want to determine the amount of memory it uses, and how much time it requires to solve a problem.

Etymology of "Algorithm"

Algorism = process of doing arithmetic using Arabic numerals.

A misperception: algiros [painful] + arithmos [number].

True origin: Abū 'Abdallāh Muhammad ibn Mūsā al-Khwārizmī was a 9th-century Persian mathematician, astronomer, and geographer, who wrote Kitab al-jabr wa'l-muqabala (Rules of restoring and equating), which evolved into today's high school mathematics text.





ITM421 Maximum contiguous subsequence sum

Given an array with integers a_1, a_2, \ldots, a_n , find the maximum value of $\sum_{k=i}^{j} a_k$.

How many possible subsequences are there?



```
maxSum = 0
for i in range(len(a)):
  for j in range(i, len(a)):
    sum = 0
    for k in range(i, j+1):
        sum += a[k]
    if sum > maxSum:
        maxSum = sum
```

Number of additions:
$$\sum_{i=0}^{n-1} \sum_{j=i}^{n-1} (j-i+1)$$

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ITM421
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```
maxSum = 0
for i in range(len(a)):
    sum = 0
    for j in range(i, len(a)):
        sum += a[j]
        if sum > maxSum:
        maxSum = sum
```

Number of additions:
$$\sum_{i=0}^{n-1} (n-i)$$



How can we apply recursion to this problem?

Split the array in the middle.

- (1) The maximal subsequence is in the left half.
- (2) The maximal subsequence is in the right half.
- (3) The maximal subsequence begins in the left half and ends in the right half.

How many additions?



ITM421 Divide and Conquer (Divide et impera)

- Split the problem into subproblems.
- Solve the subproblems recursively.
- Combine the solutions to the subproblems.



Experimental analysis of algorithms

- Write a program implementing the algorithm
- Run the program with inputs of varying size and composition
- Use a method like time.perf_counter() to get a measure of the actual running time

n	Naive	Faster	Recursive
10	2	1	1
100	760	31	19
1,000	652,285	2,411	236
10,000	_	218,210	2,378
100,000	_	23,033,000	25,037
1,000,000	_	_	260,375



Experimental analysis of algorithms

Limitations:

- It is necessary to implement the algorithm, which may be difficult.
- Results may not be indicative of the running time on other inputs not included in the experiment.
- In order to compare two algorithms, the same hardware and software environments must be used. Programming language, programming style, fine tuning should not be measured.



- Uses a high-level description of the algorithm instead of an implementation
- ullet Characterizes running time as a function of the input size n
- Takes into account all possible inputs, and looks at worst-case
- Allows us to evaluate the speed of an algorithm independent of the hardware/software environment

Theoretical analysis counts primitive operations.

Primitive operations are:

- Assigning a value to a variable
- Calling a method
- Arithmetic operations (e.g. adding two numbers)
- Indexing into an array
- Following a reference
- Returning from a method

Counting primitive operations

While we do not know the exact cost of a primitive operation (it depends on the processor speed, processor architecture, programming language, compiler, etc.), we know that all primitive operations take constant time.

There is a fixed, finite number of primitive operations. Let a be the time taken by the fastest primitive operation, let b be the time taken by the slowest primitive operation. If our algorithm uses k primitive operations, then its running time T(n) is bounded by

$$ak \le T(n) \le bk$$

Simplifying the analysis

We are more interested in the growth rate of the running time than in the exact formula. A quadratic algorithm will always be faster than a cubic algorithm if the input size is sufficiently large.

The growth rate determines the scaling behavior of an algorithm: If we increase the problem size by a factor 10, how much does the running time increase?

Or, put differently: If we buy a computer that is ten times faster, how much larger problems can we solve?

Time complexity	Problem size after speedup
\overline{n}	10s
n^2	3.16s
n^3	2.15s
2^n	s + 3.3



Since we only want to know the growth rate of an algorithm, we can simplify the analysis using Big-Oh notation.

Definition of Big-Oh:

Let f(n), g(n) be functions from $\{1, 2, 3, 4, ...\}$ to \mathbb{R} . We say that f(n) is O(g(n)) if there is a real constant c>0 and an integer $n_0\geq 1$ such that

$$f(n) \le cg(n)$$
 for $n \ge n_0$.

$$4n+1$$
 is $O(n)$

$$2n^2 + 3n + 5$$
 is not $O(n)$

$$2n^2 + 3n + 5$$
 is $O(n^2)$

We want to express the running time in the simplest possible Big-Oh notation.

 $4n \log n + 3n - 12$ is $O(n \log n + 3n)$ is correct, but we should say that it is $O(n \log n)$.

Any polynomial

$$f(n) = a_0 + a_1 n + a_2 n^2 + a_3 n^3 + \dots + a_d n^d$$

with $a_d > 0$ is just $O(n^d)$.

$$5n^2 + 3n \log n + 2n + 5$$
 is $O(n^2)$
 $20n^3 + 10n \log n + 5$ is $O(n^3)$
 $3 \log n + 2$ is $O(\log n)$
 2^{n+2} is $O(2^n)$
 $2n + 100 \log n$ is $O(n)$



The asymptotic analysis of an algorithm determines the running time in big-Oh notation.

To perform the asymptotic analysis

- We find the worst-case number of primitive operations executed as a function of the input size
- We express this function with big-Oh notation
 Since constant factors and lower- order terms are eventually dropped anyhow, we can disregard them when counting primitive operations

A word of caution: What is better, $10^{100}n$, n^{100} , or 2^n ?

Keeping your perspective

- Throughout the course of an analysis, keep in mind that you are interested only in significant differences in efficiency
- When choosing an ADT implementation, consider how frequently particular ADT operations occur in a given application
- Some seldom-used but critical operations must be efficient
- If the problem size is always small, you can probably ignore an algorithm's efficiency
- Weigh the trade-offs between an algorithm's time requirements and its memory requirements