

by habib

Outline

- Why we care
- What it be
- How we calculate it
- Examples
- Future readings



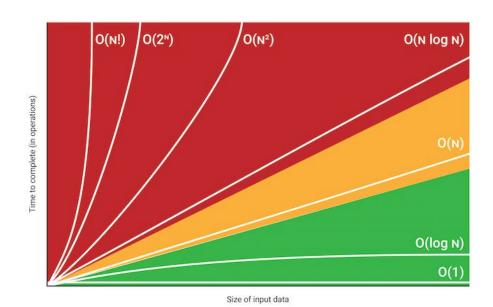
Why we care



- CLRS: "Using O-notation, we can often describe the running time of an algorithm merely by inspecting the algorithm's overall structure"
- Cracking the Coding interview: "Big O time is the language and metric we use to describe the efficiency of algorithms. Not understanding it thoroughly can really hurt you in developing an algorithm"
- Not everyone's computer is the same!
 - o If program runs well on your good computer, might not work as well on someone's much slower computer
- Basically tells us how our algorithms run, and how they will scale with different conditions

What it be

- Big O, big omega, big theta
 - time complexity
 - space complexity
- Represented by O(s)
 where s = some equation
 describing # of operations
- n usually refers to input size
- O(n) can be faster than O(1) but on average it's slower!



How we calculate it (ground rules)

- Best, worst, and expected case
 - really just care about the worst and expected case
 - worst: choose biggest pivot repeatedly in quick sort
- Drop non-dominant terms
 - \circ O(2n) = O(n)
 - \circ O(n³ + n² + n¹) = O(n³)
- Each line is one operation
 - Add if operation A then B
 - Multiply if operation A executed B times

```
## add case
4    arr_a = [1, 2, 3, 4, 5]
5    arr_b = [5, 4, 3, 2, 1]
6    count = 0
7    for elem_a in arr_a:
8         count += 1
9         print(elem_a)
10
11    for elem_b in arr_b:
12         count+= 1
13         print(elem_b)
14    print(count)
```

```
17  ## multiply case
18  arr_a = [1, 2, 3, 4, 5]
19  arr_b = [5, 4, 3, 2, 1]
20  count = 0
21  for elem_a in arr_a:
22     for elem_b in arr_b:
23         print(elem_a, ",", elem_b)
24         count += 1
25  print(count)
26
```

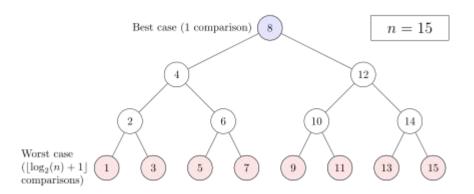
How we calculate it (space)

- Same idea as runtime
- Talk about this when we deal with recursion OR dealing with extra space (maps, stacks, arrays, etc...)
- One recursive call -> one level to system stack

```
def multiplication(multiplicand, multiplier):
    if multiplier <= 0:
        return 0
    return multiplicand + multiplication(multiplicand, multiplier - 1)
    print(multiplication(2,3))</pre>
```

How we calculate it (log runtimes)

- Dividing input size by half each step leads to log(n) run time
- Examples:
 - Binary search has O(log(n)) runtime
 - Merge sort has O(n * log(n)) runtime



Examples (what are these run times?)

Examples (what are these run times?) cont.

```
61  ## printing numbers with a twist
62  arr_a = [1, 2, 3, 4, 5, 6, 7]
63  arr_store = []
64
65  for i in range(len(arr_a)):
66     for j in range(len(arr_a) // 2):
67         arr_store.append(arr_a[j] + arr_a[i])
68         print(arr_a[i], arr_a[j] + arr_a[i])
69
70  print(arr_store)
```

```
69  def fib(number):
70          if number <= 1:
71              return 1
72          return fib(number - 1) + fib(number - 2)
73
74          print(fib(5))
75</pre>
```

Examples

- Which one of these has a run time of O(N)?
 - \circ O(N + M)
 - o O(2^N)
 - \circ O(N + N/2)
 - \circ O(N + log(N))
 - \circ O(2N + 3)
- What's the run time of the factorial function?

```
76
77  def factorial(number):
78    if n < 0:
79        return -1
80    elif n == 0:
81        return 1
82    else:
83        return factorial(n - 1) * n
84
85  print(factorial(4)) # 4! = 4 * 3 * 2 * 1 = 24
86</pre>
```

Examples (gimme gimme)

Future readings

- CLRS Big algorithm textbook from the late 80's
- Cracking the coding interview helpful review of data structures and algorithms
- Abdul Bari algorithms series