Introduction and Big-O notation

Bronson Rudner

South African Programming Olympiad Training Camp

December 12, 2020

Introduction and Big-O notation

What do I need to know to solve programming problems?

What do I need to know to solve programming problems?

• Basic coding skills and fluency

- Basic coding skills and fluency
- Knowledge of algorithms and data structures

- Basic coding skills and fluency
- Knowledge of algorithms and data structures
- Ability to problem solve

< 円

• Learning to code these will ensure you develop your basic coding skills and fluency

- Learning to code these will ensure you develop your basic coding skills and fluency
- Many problems reduce to one of, or some subset of these

- Learning to code these will ensure you develop your basic coding skills and fluency
- Many problems reduce to one of, or some subset of these
- They provide inspiration for further solutions

- Learning to code these will ensure you develop your basic coding skills and fluency
- Many problems reduce to one of, or some subset of these
- They provide inspiration for further solutions
- Serve as a guideline for solving problems efficiently

Ad-Hoc

- Oreedy
- Omputational Geometry
- Oynamic Programming
- 6 BigNums
- Two-Dimensional
- 🗿 Eulerian Path
- Minimum Spanning Tree

- In Knapsack
- Network Flow
- Flood Fill
- Shortest Path
- Approximate Search
- Complete Search
- Recursive Search Techniques
- 4 Heuristic Search

• Computers are fast - but their speed is still finite

- Computers are fast but their speed is still finite
- On the order of $100\,000\,000$ operations per second (C++)

- Computers are fast but their speed is still finite
- On the order of $100\,000\,000$ operations per second (C++)
- Java about 2x slower, Python about 10x slower (and Scratch is about 100x slower)

- Computers are fast but their speed is still finite
- \bullet On the order of 100 000 000 operations per second (C++)
- Java about 2x slower, Python about 10x slower (and Scratch is about 100x slower)
- It isn't enough to find an algorithm that solves a problem

- Computers are fast but their speed is still finite
- \bullet On the order of 100 000 000 operations per second (C++)
- Java about 2x slower, Python about 10x slower (and Scratch is about 100x slower)
- It isn't enough to find an algorithm that solves a problem
- It needs to solve it within the time limit

• The Fibonacci series is given by

 $1, 1, 2, 3, 5, 8, \ldots$

where the next number in the sequence is given by the sum of the two preceding numbers

• The Fibonacci series is given by

 $1, 1, 2, 3, 5, 8, \ldots$

where the next number in the sequence is given by the sum of the two preceding numbers

• Find the n^{th} Fibonacci number, given that $1 \le n \le 1000$

The Fibonacci series is given by

 $1, 1, 2, 3, 5, 8, \ldots$

where the next number in the sequence is given by the sum of the two preceding numbers

• Find the n^{th} Fibonacci number, given that $1 \le n \le 1000$

```
• def slow_fibonacci(n):
    if n == 1 or n == 2:
        return 1
    else:
        return slow_fibonacci(n-1) + slow_fibonacci(n-2)
```

• The Fibonacci series is given by

 $1, 1, 2, 3, 5, 8, \ldots$

where the next number in the sequence is given by the sum of the two preceding numbers

• Find the n^{th} Fibonacci number, given that $1 \le n \le 1000$

```
• def slow_fibonacci(n):
    if n == 1 or n == 2:
        return 1
    else:
        return slow_fibonacci(n-1) + slow_fibonacci(n-2)
```

 Increasing n by 1, (roughly) doubles the total number of calls of slow_fibonacci. The Fibonacci series is given by

 $1, 1, 2, 3, 5, 8, \ldots$

where the next number in the sequence is given by the sum of the two preceding numbers

• Find the n^{th} Fibonacci number, given that $1 \le n \le 1000$

```
• def slow_fibonacci(n):
    if n == 1 or n == 2:
        return 1
    else:
```

return slow_fibonacci(n-1) + slow_fibonacci(n-2)

- Increasing n by 1, (roughly) doubles the total number of calls of slow_fibonacci.
- n = 40 calls slow_fibonacci about 200 000 000 times!

• Gives a rough idea of the runtime of a program / function

< 1 k

- Gives a rough idea of the runtime of a program / function
- Is expressed in relation to the size of the input (n).

- Gives a rough idea of the runtime of a program / function
- Is expressed in relation to the size of the input (n).
- If a program is O(f(n)), we mean it takes no more than C · f(n) steps in total, for suitably large n (for some constant C).

- Gives a rough idea of the runtime of a program / function
- Is expressed in relation to the size of the input (n).
- If a program is O(f(n)), we mean it takes no more than $C \cdot f(n)$ steps in total, for suitably large n (for some constant C).
- In particular, if a program takes T(n) steps, it is O(T(n)).

It is an upper bound:

$$n = O(n^2), n^2 = O(n^2), 1 = O(n)$$

• • • • • • • •

æ

It is an upper bound:

$$n = O(n^2), n^2 = O(n^2), 1 = O(n)$$

We ignore constant factors:

$$3n^2 = O(n^2), \quad \frac{1}{2}n = O(n)$$

It is an upper bound:

$$n = O(n^2), n^2 = O(n^2), 1 = O(n)$$

We ignore constant factors:

$$3n^2 = O(n^2), \quad \frac{1}{2}n = O(n)$$

We only care about the largest term:

$$n^{2} + n = O(n^{2}), \quad 2n^{2} + 3n + 1000 = O(n^{2})$$

• We usually consider the worst case bound

• E.g. linear search can be O(1) in the best case, but in the worst case, and on average, it is O(n)

- We usually consider the worst case bound
 - E.g. linear search can be O(1) in the best case, but in the worst case, and on average, it is O(n)
- If you are sure the data is suitably random, you could use average time bound

- We usually consider the worst case bound
 - E.g. linear search can be O(1) in the best case, but in the worst case, and on average, it is O(n)
- If you are sure the data is suitably random, you could use average time bound
- Can also describe memory of a program but usually you are given more memory than the time bound anyway

```
def triangular_nums(n):
    nums = []
    for i in range(n):
        num = 0
        for j in range(i+1):
            num += j+1
        nums.append(num)
    return nums
```

э

```
def triangular_nums(n):
    nums = []
    for i in range(n):
        num = 0
        for j in range(i+1):
            num += j+1
        nums.append(num)
    return nums
Answer: O(n<sup>2</sup>)
```

э

```
def is_prime(n):
    if n % 2 == 0:
        return False
    i = 3
    while i * i <= n:
        if n % i == 0:
            return False
        i += 2
    return True
```

< 4[™] >

3

```
def is_prime(n):
    if n % 2 == 0:
        return False
    i = 3
    while i * i <= n:
        if n % i == 0:
             return False
        i += 2
    return True
Answer: O(\sqrt{n})
```

< 1 k

3

```
def foo(nums1, nums2):
   total = 0
   for x in nums1:
      total += x
   for x in nums1:
      for y in nums2:
        total += x * y
   return total
```

э

```
def foo(nums1, nums2):
    total = 0
    for x in nums1:
        total += x
    for x in nums1:
        for y in nums2:
            total += x * y
    return total
```

Answer: O(nm) (where n, m is the size of nums1, nums2, respectively)

```
def sum_powers_of_two(n):
    total = 0
    i = 1
    while i < n:
        total += i
        i *= 2
    return total
```

< 1 k

э

```
def sum_powers_of_two(n):
    total = 0
    i = 1
    while i < n:
         total += i
         i *= 2
    return total
Answer: O(\log n)
(\log 2^{x} = x \text{ (base 2)})
```

э



```
What is the Big-O of the following function?
def slow_fibonacci(n):
    if n == 1 or n == 2:
        return 1
    else:
        return slow_fibonacci(n-1) + slow_fibonacci(n-2)
```

3



```
def slow_fibonacci(n):
    if n == 1 or n == 2:
        return 1
    else:
        return slow_fibonacci(n-1) + slow_fibonacci(n-2)
Answer: O(2<sup>n</sup>)
```

3



```
def slow_fibonacci(n):
    if n == 1 or n == 2:
        return 1
    else:
        return slow_fibonacci(n-1) + slow_fibonacci(n-2)
Answer: O(2<sup>n</sup>)
(can be tightened to O(1.618<sup>n</sup>))
```

3

```
def sum_values_in_binary_tree(node):
```

```
sum = node.value
```

if node.left is not None:

```
sum += sum_values_in_binary_tree(node.left)
if node.right is not None:
    sum += sum_values_in_binary_tree(node.right)
return sum
```

What is the Big-O of the following function?
def sum_values_in_binary_tree(node):
 sum = node.value
 if node.left is not None:
 sum += sum_values_in_binary_tree(node.left)
 if node.right is not None:
 sum += sum_values_in_binary_tree(node.right)
 return sum

Answer: O(n) (where n is the number of nodes in the tree)

э

• Determine the Big-O of your algorithm. E.g. $O(nk \log n)$.

- Determine the Big-O of your algorithm. E.g. $O(nk \log n)$.
- Plug in the constraints of the question. E.g. $n \le 10\,000, k \le 50$. Then $nk \log n \approx (10\,000)(50)(13) = 6\,500\,000$

- Determine the Big-O of your algorithm. E.g. $O(nk \log n)$.
- Plug in the constraints of the question. E.g. $n \le 10\,000, k \le 50$. Then $nk \log n \approx (10\,000)(50)(13) = 6\,500\,000$
- Your result should be reasonable amount less than 100 000 000 typically less than 10 000 000 is reasonable. You may multiply this 10 000 000 by the time limit in seconds.

Class	Big-O	Typical upper limit on <i>n</i>	n = 1000000
Constant	1		1
Logarithmic	log n		20
Square root	\sqrt{n}	10 ¹³	1000
Linear	п	5 000 000	
Linearithmic	n log n	200 000	
Quadratic	n ²	5 000	
Cubic	n ³	200	
Exponential	2 ⁿ	24	
Factorial	n!	11	

< 47 ▶

æ