App Academy

Big O Analysis

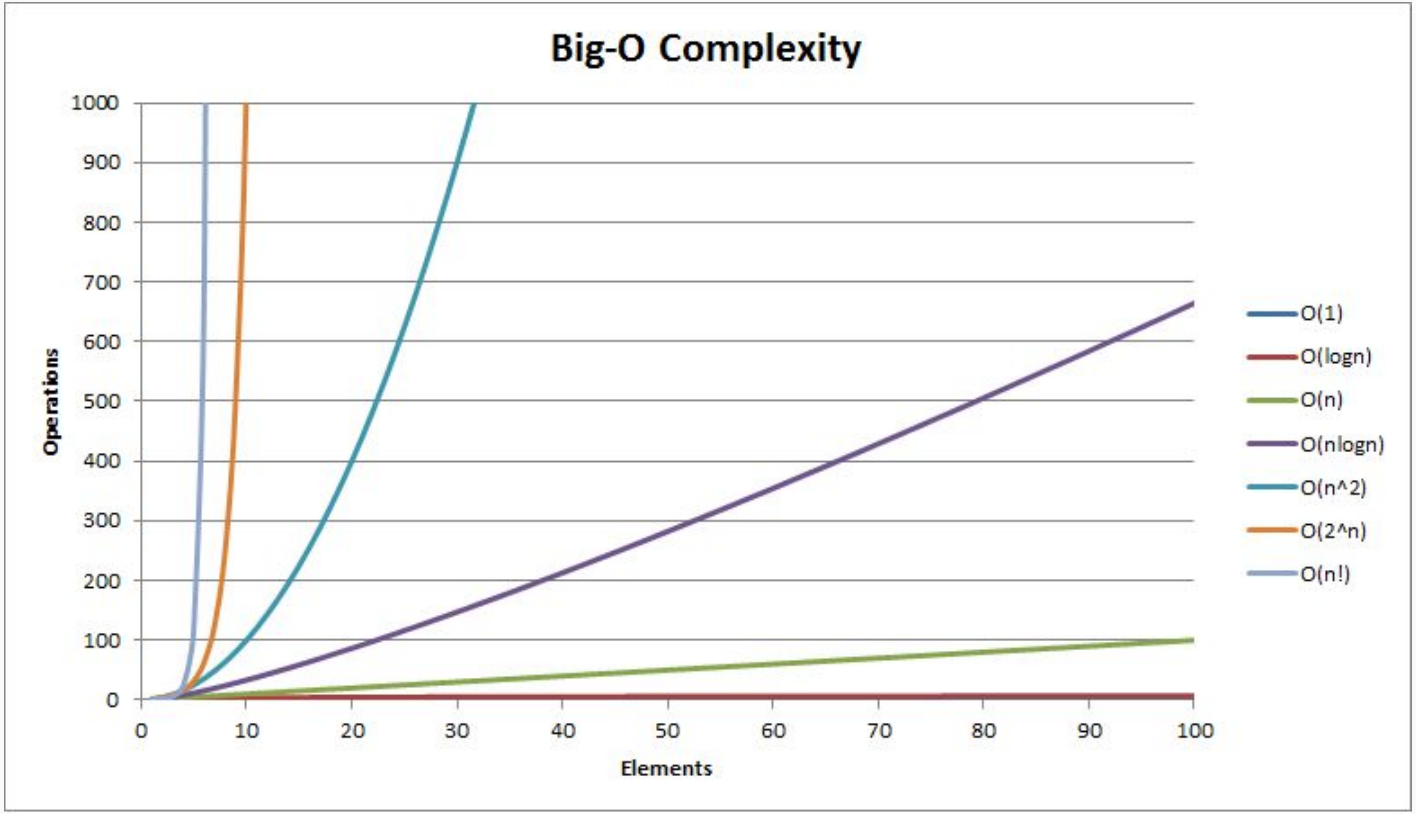
Big O Analysis

- Big O is how we analyze how efficient our solutions are
- This helps us understand how well our solutions work at scale
- There are two things we want to analyze:
  - time
  - space
- Generally, we are more concerned with time, but it is still important to understand how to analyze space efficiency as well.
- We are usually talking about worst case scenario
  - There are a few niche cases where we take the average into consideration instead. This is called "amortized complexity". Inserting elements into dynamic arrays are an example of this.

Big O Rules

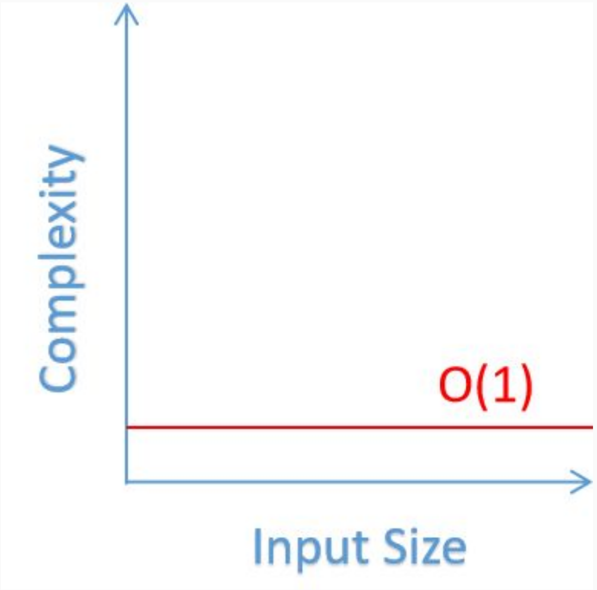
- Dropping constants
  - O(2n) is effectively the same as O(n) at large inputs
- Dropping non-dominant terms
  - O(n + log(n)) can be simplified to O(n) since O(n) is slower than O(log(n))
- Amortized time
  - Dynamic Array Example:
    - Arrays must be resized when reaching capacity, which is an O(n) operation.
    - However, this doesn't happen often.
    - If the vast majority of the time we can expect a O(1) push time complexity, we can amortize the runtime to O(1) even if the worst case is O(n).
- When figuring out complexities, ask yourself: How do my operations scale as my input gets larger?
- Always always ALWAYS define your variables. The correctness of your analysis is dependent on how you define your variables.

Big O Chart


Big-O Complexity
Operations
1000
900
800
700
600
500
400
300
200
100
0
0
10
20
30
40
50
60
70
80
90
100
Elements
O(1)
O(logn)
O(n)
O(nlogn)
O(n^2)
O(2^n)
O(n!)

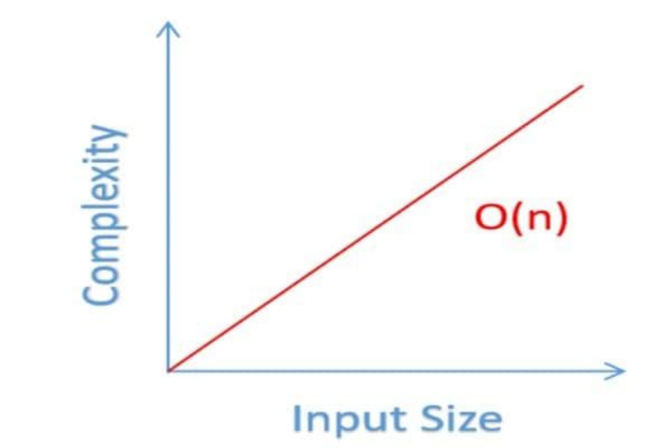
O(1) - constant

- O(1) is the most optimal complexity possible
- No matter how our input grows, our number of operations is the same
- This is represented by a flat line
- Examples:
  - Arrays
    - nums = [1,2,3]
    - nums.push(4) // pushing to end of array
    - nums.pop() // popping from end of array
    - nums[0] // lookup
  - Hash Maps / Sets
    - hash = {}
    - hash["key"] = 10 // insert
    - "key" in hash // lookup
    - hash["key"] // lookup



O(n) - linear

- As our input size grows, our operations grow proportionally
- Note: nested loops can still be O(n); e.g. sliding window
- Examples:
    - Arrays
        - nums = [1, 2, 3]
        - nums.forEach() // looping
        - 2 in nums // searching
        - nums.shift() // removing from beginning



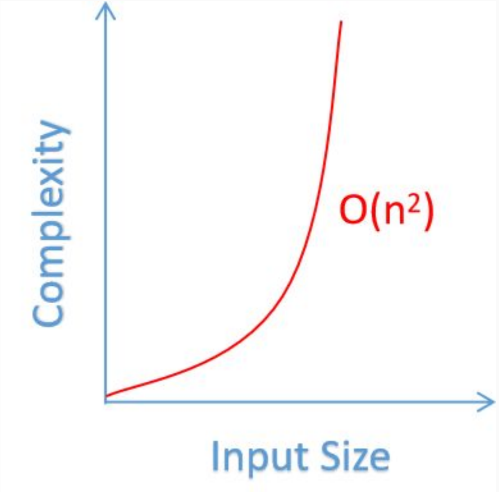
$O(n^2)$ - quadratic

- As our input grows, our operations grow quadratically
- Examples:
    - Traversing a square matrix
        - nums = [[1,2,3], [4,5,6], [7,8,9]]
        - for (let row=0; row<nums.length; row++) {

          for (let col=0; col<nums[0].length; col++) {

          console.log(nums[row][col]);

          }



O(n*m)

- Just because we have nested loops does not mean $O(n^2)$!!!
- WE MUST DEFINE OUR VARIABLES
- Example
    - Traversing a rectangle matrix
        - nums = [[1,2,3,4], [5,6,7,8], [9,10,11,12]]
        - for (let row=0; row<nums.length; row++) {

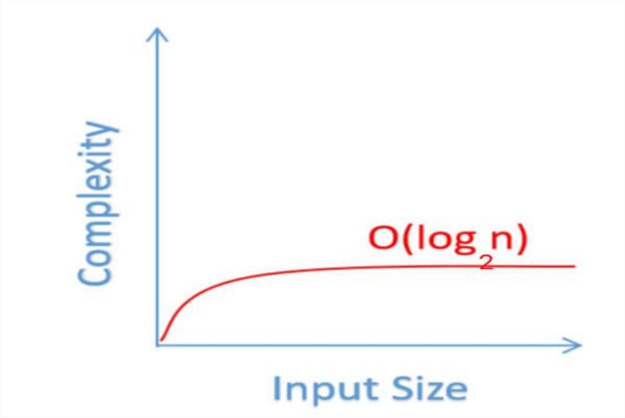
```
    for (let col=0; col<nums[0].length; col++) {
        console.log(nums[row][col]);
}
```

$O(n^3)$

- Examples
  - Finding all substrings in a string
    - s = "string"
    - ```
      for (let i=0; i<s.length; i++) {
          for (let j=0; j<s.length; j++) {
              console.log(s.slice(i, j+1))
          }
      }
      ```
      ```

O(log(n)) - logrithmic

- As our input size grows, our operations grow logarithmically
- Marginally more efficient than O(1) but much more efficient than O(n)
- Examples
  - Binary Search
    - ```
      function search(root, target) {
          if (!root) return false;
          if (target < root.val) {
              return search(root.left, target);
          } else if (target > root.val) {
              return search(root.right, target);
          } else {
              return true
      }
      ```
  - Pushing and popping from heaps


      ```

$O(n*\log(n))$

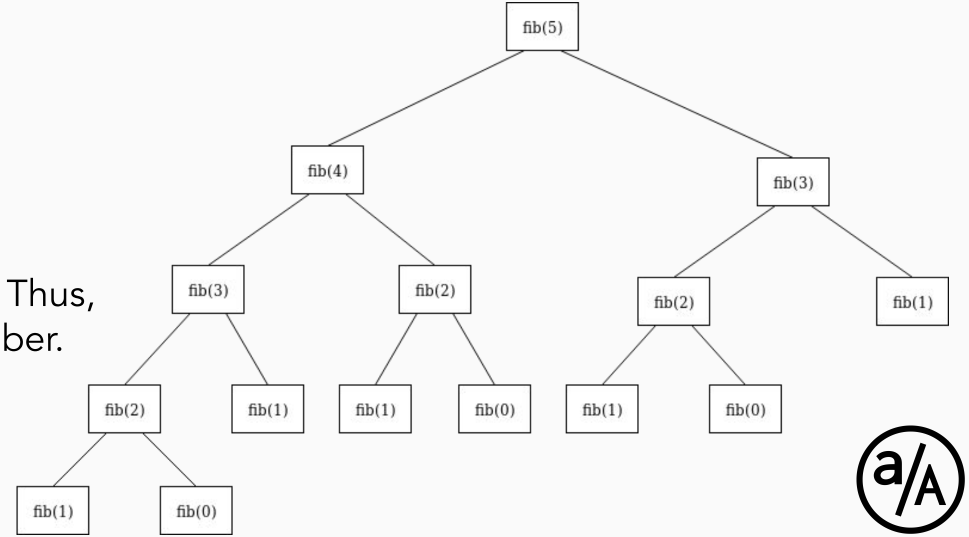
- Marginally more inefficient than $O(n)$ but much more efficient than $O(n^2)$.
- Examples:
  - Merge sort
  - Most built in sorting functions

$O(2^n)$ - exponential

- Most common with multi-path recursion
- Multi-path recursive functions can be analyzed with the following formula:

$$(\text{\# of paths})^{(\text{depth of stack})}$$

- The tree on the right represents a recursive Fibonacci function.
- Each node has at most 2 branching paths.
- The depth of the stack is 5, which is the input. Thus, we can call this $O(2^n)$ where n is our input number.



O(n!)

- Very rare and is unlikely to come up with an interview problem
- Horribly inefficient- the worst of the worst case scenarios
- The only problems that require this are very difficult problems that are considered "NP-complete" - nondeterministic polynomial-time complete
- Not necessary to put too much focus here, but you can read this article if you are interested.
- Examples
  - finding all permutations
  - "traveling salesman problem"

Questions?