

# BIG O

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*Give it to me straight, doc; How bad is it?: Or measuring the efficiency of the code*







# LEARNING OBJECTIVES

- By the end of this we will be able to:
  - Define what Big O is and why it's important
  - Calculate Big O for some simple algorithms
  - Be able to compare different time complexities
  - Calculate Big O for recursive algorithms
  - Calculate Big O for multi-level algorithms
  - Understand Big O in the context of time and space

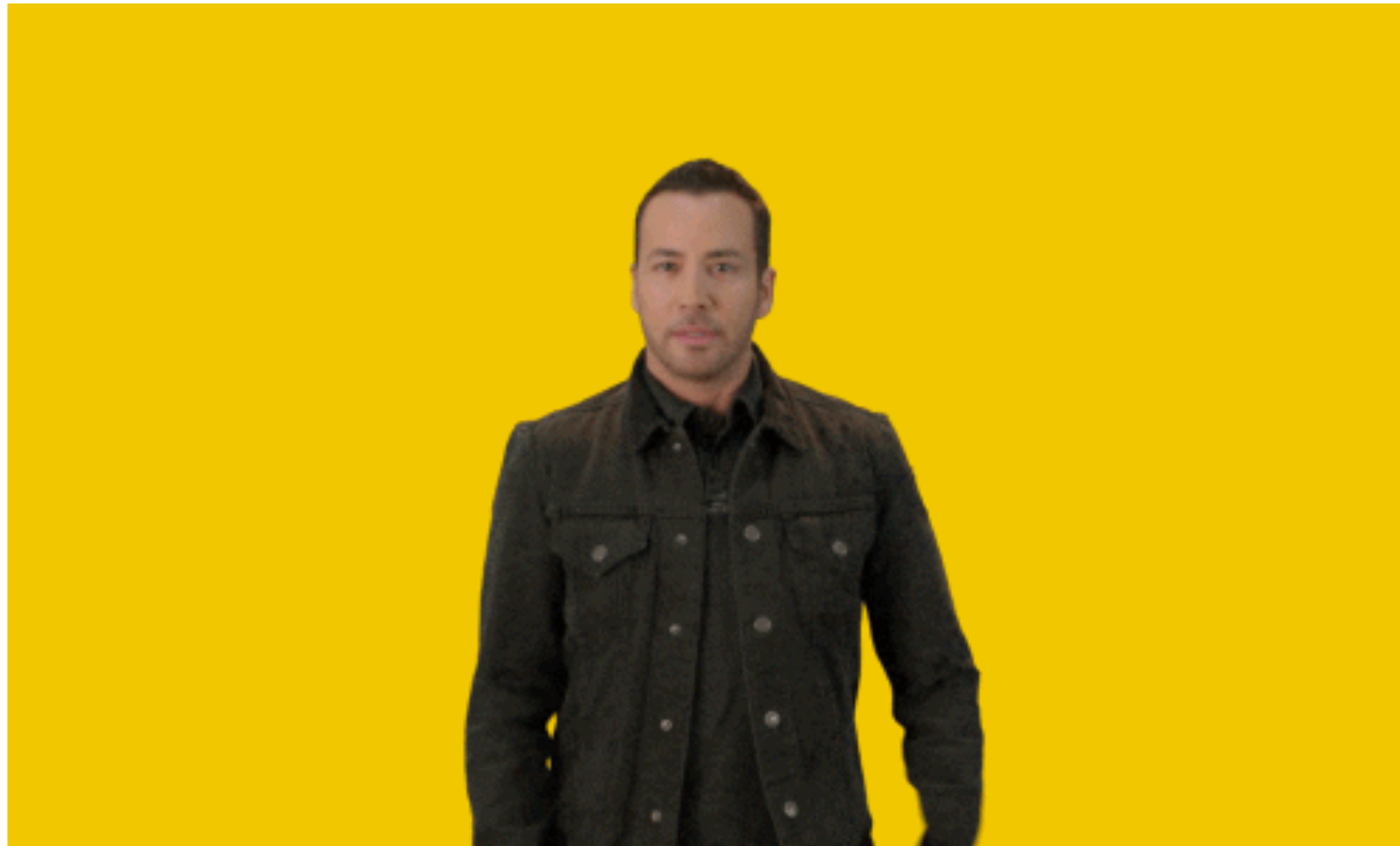
# MEASURING PERFORMANCE: SUM UP THE NUMBERS FROM 1 TO N INCLUSIVE

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REPLIT



# DISCUSSION: WHY CAN'T WE JUST BENCHMARK?



# SO WHAT IS BIG O?

**THE ANALYSIS OF HOW MUCH TIME  
(OR SPACE) AN ALGORITHM TAKES  
UP, RELATIVE TO ITS INPUT, AS THAT  
INPUT GETS BIGGER AND BIGGER**

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THE ANALYSIS OF HOW MUCH TIME  
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UP, **RELATIVE TO ITS INPUT, AS THAT  
INPUT GETS BIGGER AND BIGGER**

# SO WHAT IS BIG O?

- How the runtime (or space) requirements grow...
  - A whole bunch of external factors are important when measuring the speed of an algorithm; so instead of using an absolute measure of speed, we use Big O Notation to express how quick it grows
- ... Relative to the input
  - Since we are not looking for an absolute number, we need to measure speed relative to something; so we measure speed relative to the change in size of input



# SO WHAT IS BIG O?

- The letter 'O' is used because the growth rate of a function is also called the 'order of the function'
- Refers to worst case scenario

# WHY SHOULD WE CARE?

- Being able to evaluate the runtime/space complexity of an algorithm is critical to writing performant code
- When asked to optimize an algorithm, one of the first things you might do is determine its Big O complexity
- Most importantly, it comes up in interviews



# SOME BASIC STRATEGIES

- Measure the complexity at every step of the algorithm - We should ask ourselves, “Would this change if the input got larger?”
- Add the complexity for each line at the same level of indentation, multiple inner levels by their outer levels
  - Nested loops -> multiply
  - Scoped/Sibling loops -> add
- Simplify your terms, then drop everything by the largest term



# SOME EXAMPLES

- Example 1
- Example 2
- Example 3
- Example 4

# Beyond the Basics

- Recursion
- Space Complexity
- Multivariate algorithms

# RECURSION WARMUP

# Recursion

- It's helpful to think of recursion as a tree
- When there is only one “branch” of recursion, this is usually like a standard “for” loop, where the number of times we recursive corresponds to the input size
- When there are multiple recursive branches, the runtime will often be similar to  $O(\text{branches}^{\text{depth}})$ 
  - Each level of “depth” has “branch” number more calls than the level before - an exponential relationship!



**WE ARE GIVEN A SET OF N STAIRS. THERE IS A PERSON STANDING AT THE BOTTOM. THIS PERSON CAN ONLY CLIMB EITHER 1 OR 2 STAIRS AT A TIME. COUNT THE NUMBER OF WAYS THIS PERSON CAN REACH THE TOP OF THE STAIRS**

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*REPLIT*

```
function fib (n) {  
  if (n === 1 || n === 0) return n;  
  else return fib(n - 1) + fib(n - 2);  
}
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fib(4)



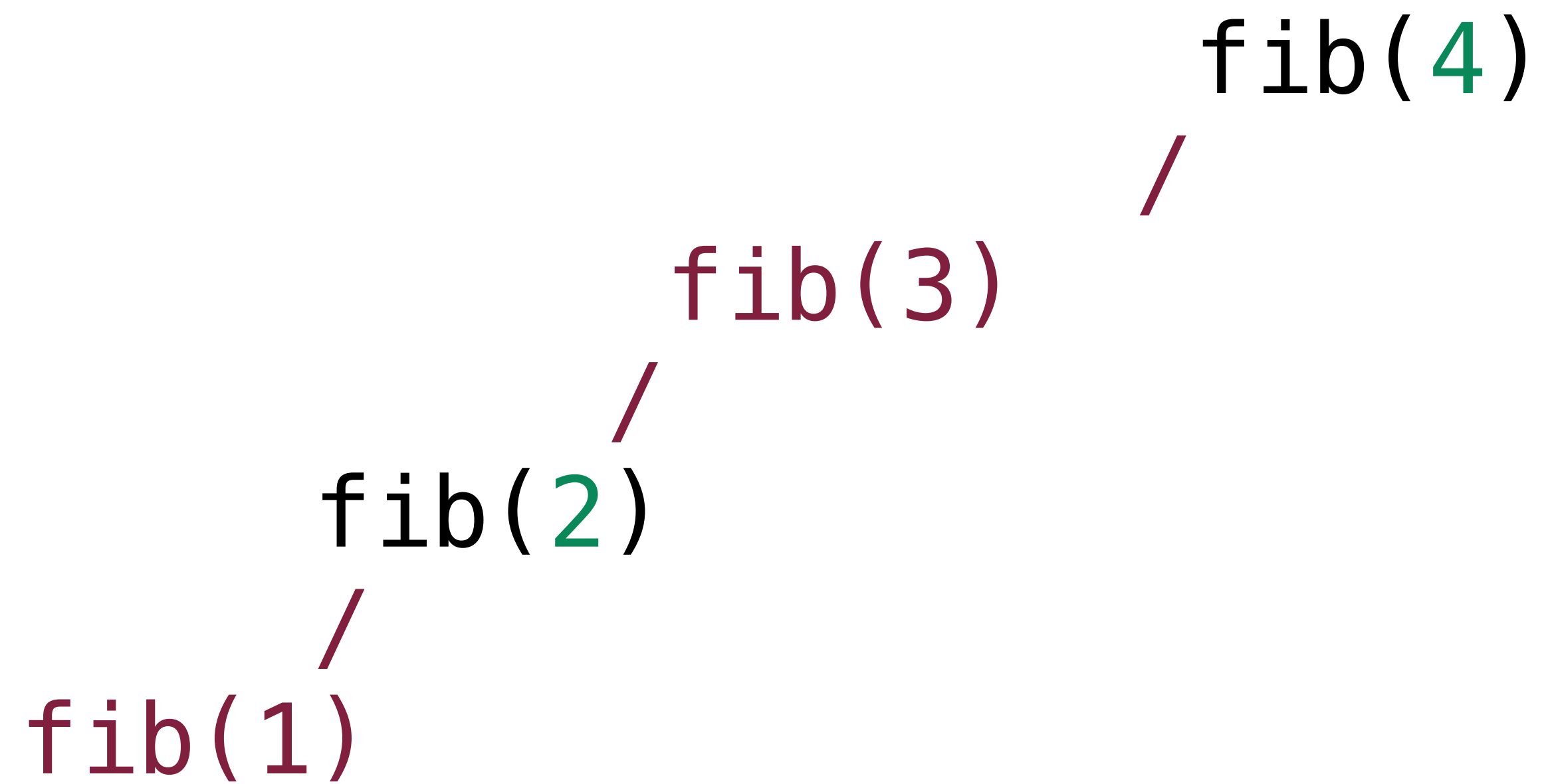
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fib(4)  
/  
fib(3)

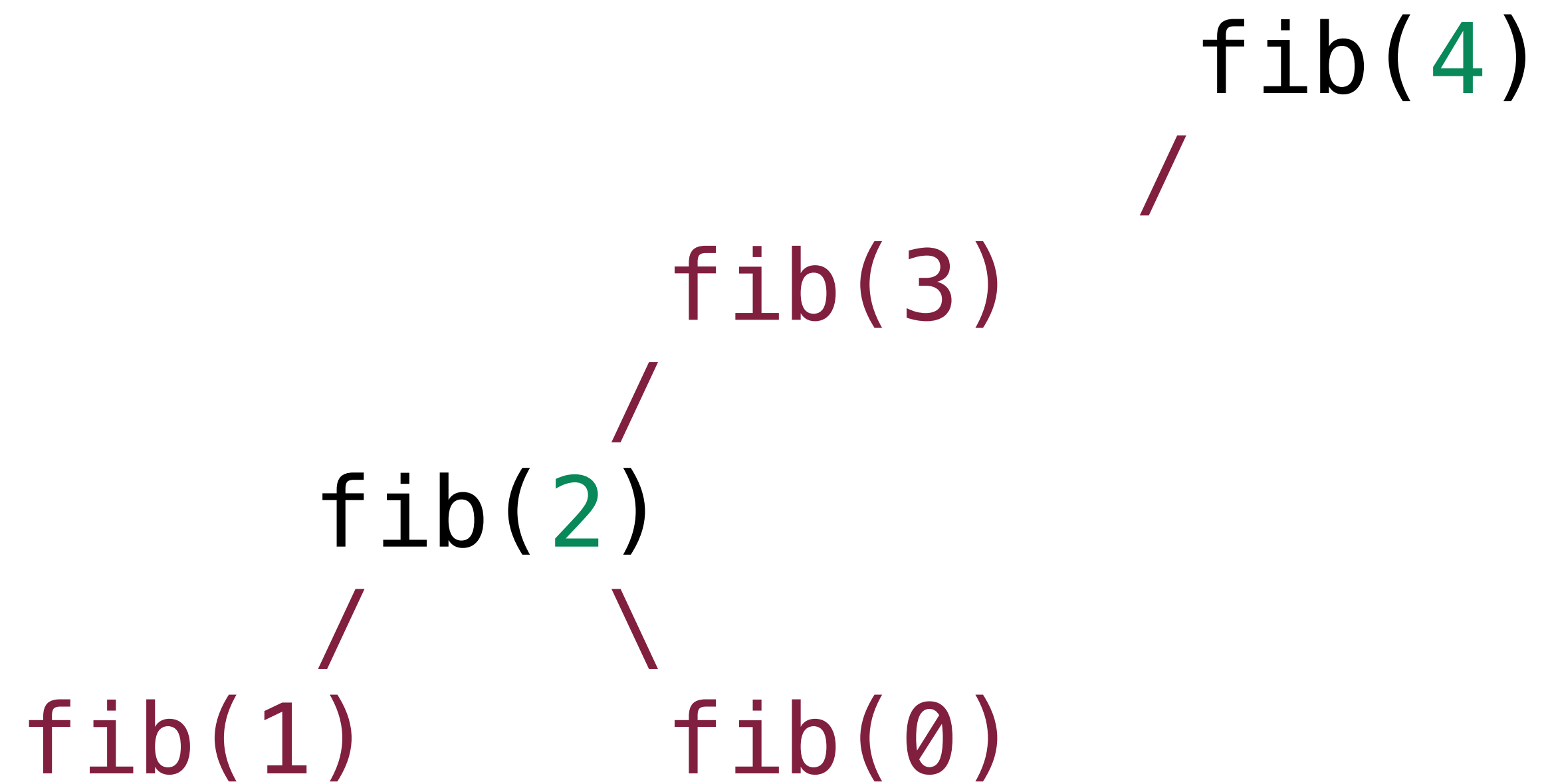
```
function fib (n) {  
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}
```

fib(2) / fib(3) / fib(4)

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}
```

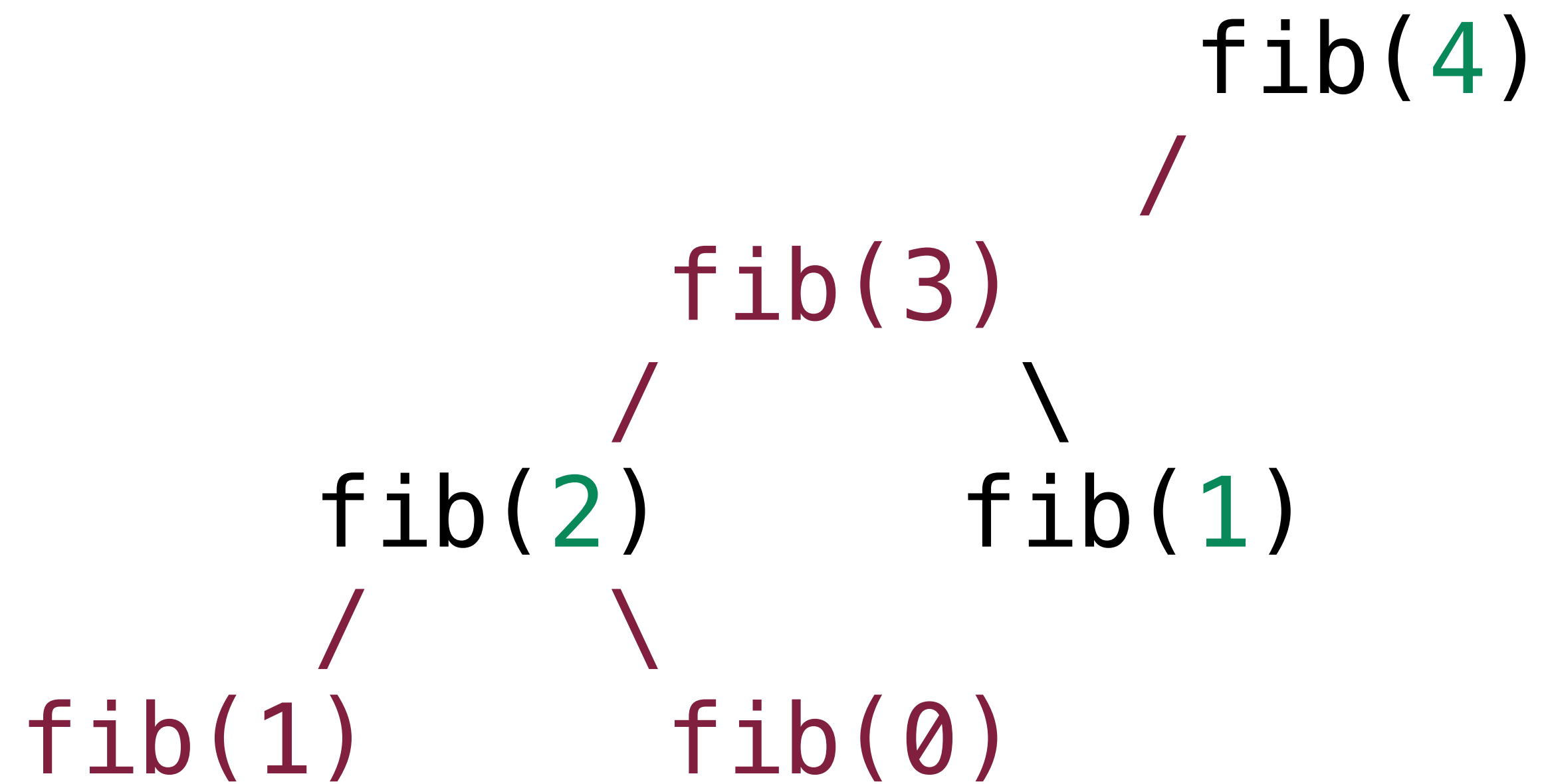


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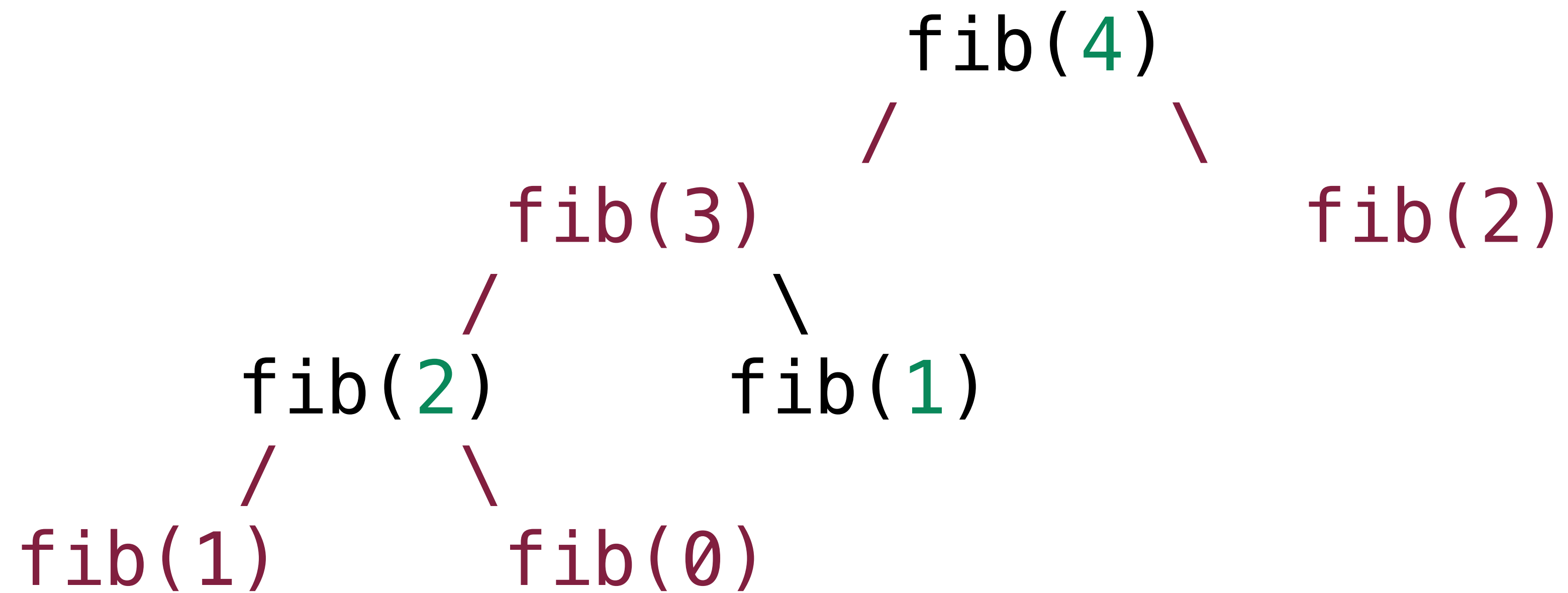




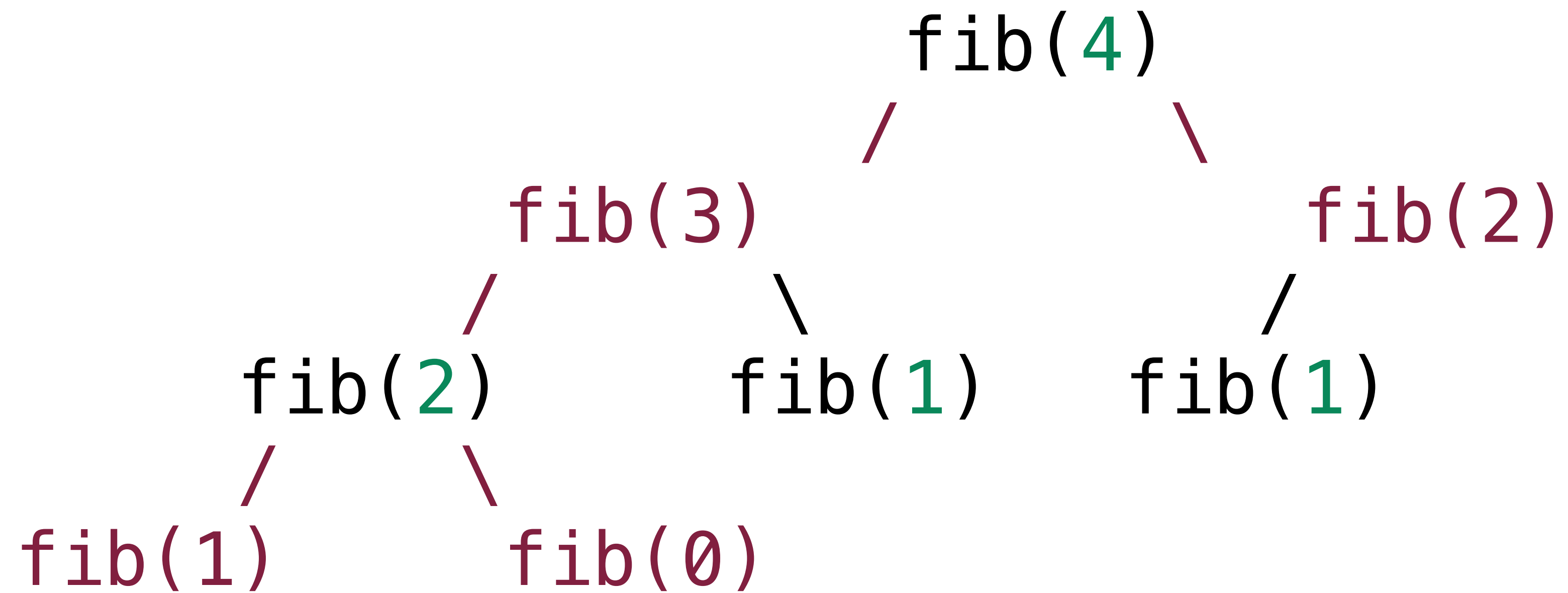
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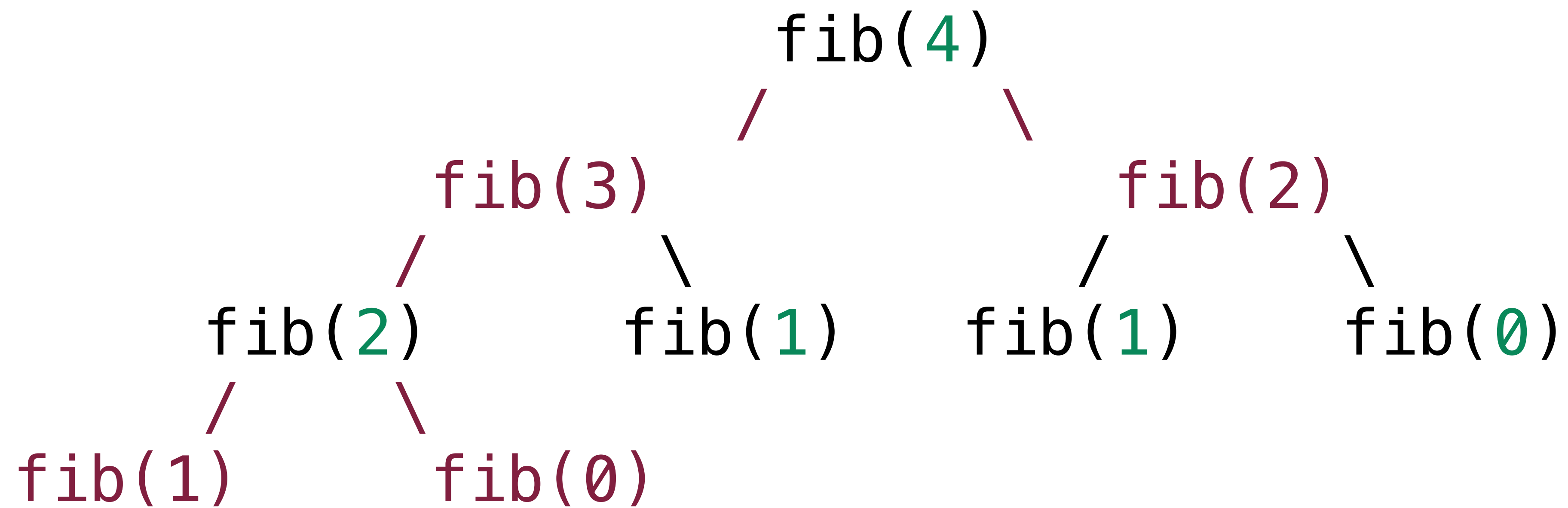
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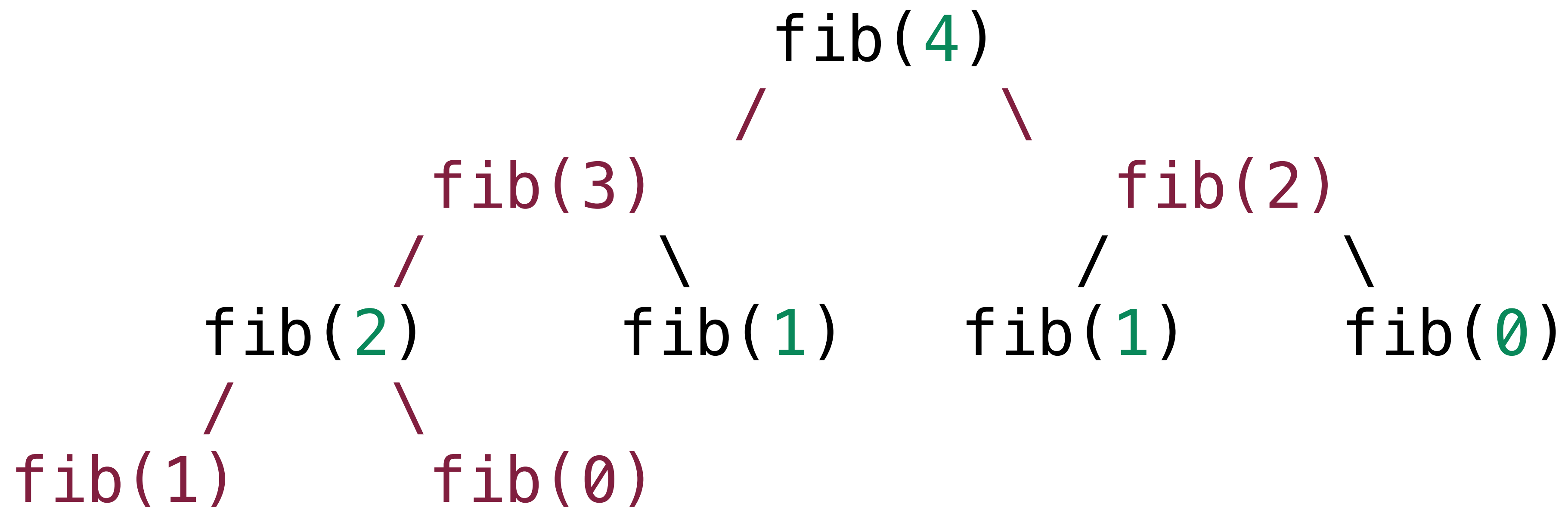
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function fib (n) {
  if (n === 1 || n === 0) return n;
  else return fib(n - 1) + fib(n - 2);
}
```

our input is equal to 4:  $n = 4$

we go four levels deep, so depth =  $n$

we branch twice with each recursive call

therefore, runtime is  $O(2^n)$ !





# WOW, THAT'S TEARABLE





**BUT SERIOUSLY, LET'S MAKE IT BETTER**

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*REPLIT*

```
function fib (n, memo = {}) {  
  if (n === 1 || n === 0) return n;  
  else if (memo[n]) return memo[n];  
  else memo[n] = fib(n - 1, memo) + fib(n - 2, memo);  
  return memo[n];  
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function fib (n, memo = {}) {  
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```
memo = {  
  
}
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fib(4)

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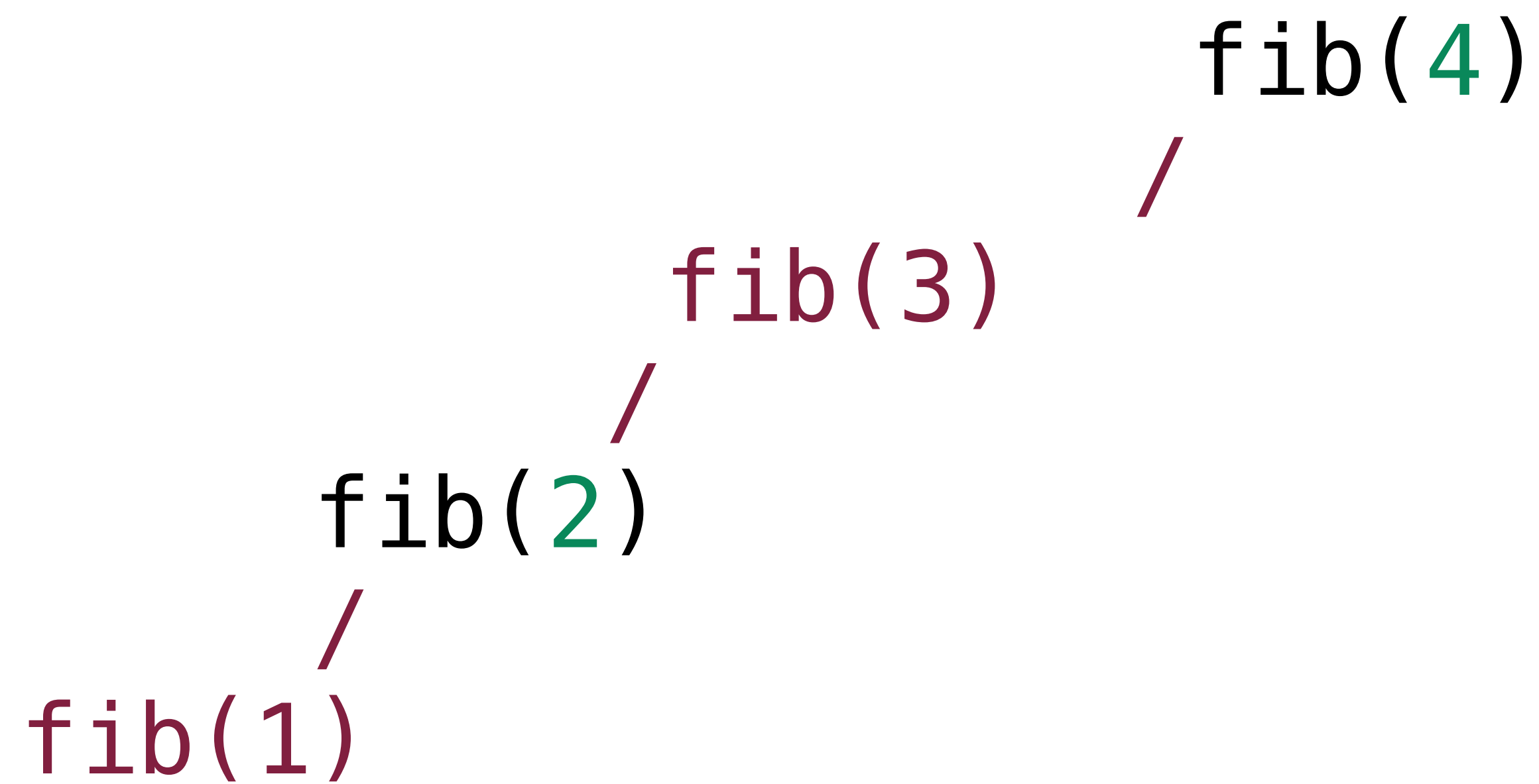
```
memo = {  
  
}
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fib(4)  
/  
fib(3)  
/  
fib(2)

```
function fib (n, memo = {}) {
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  else memo[n] = fib(n - 1, memo) + fib(n - 2, memo);
  return memo[n];
}
```

```
memo = {
  }

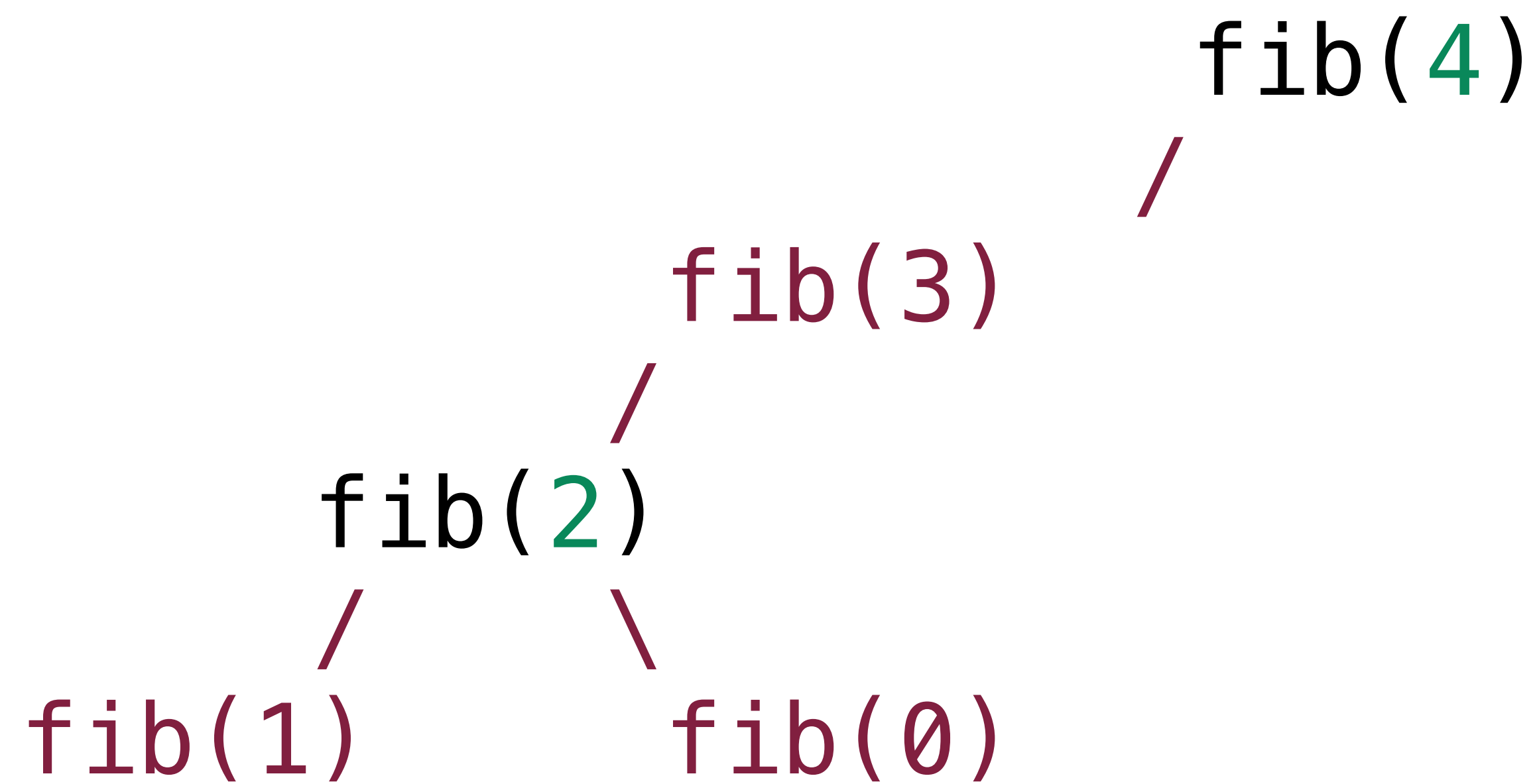
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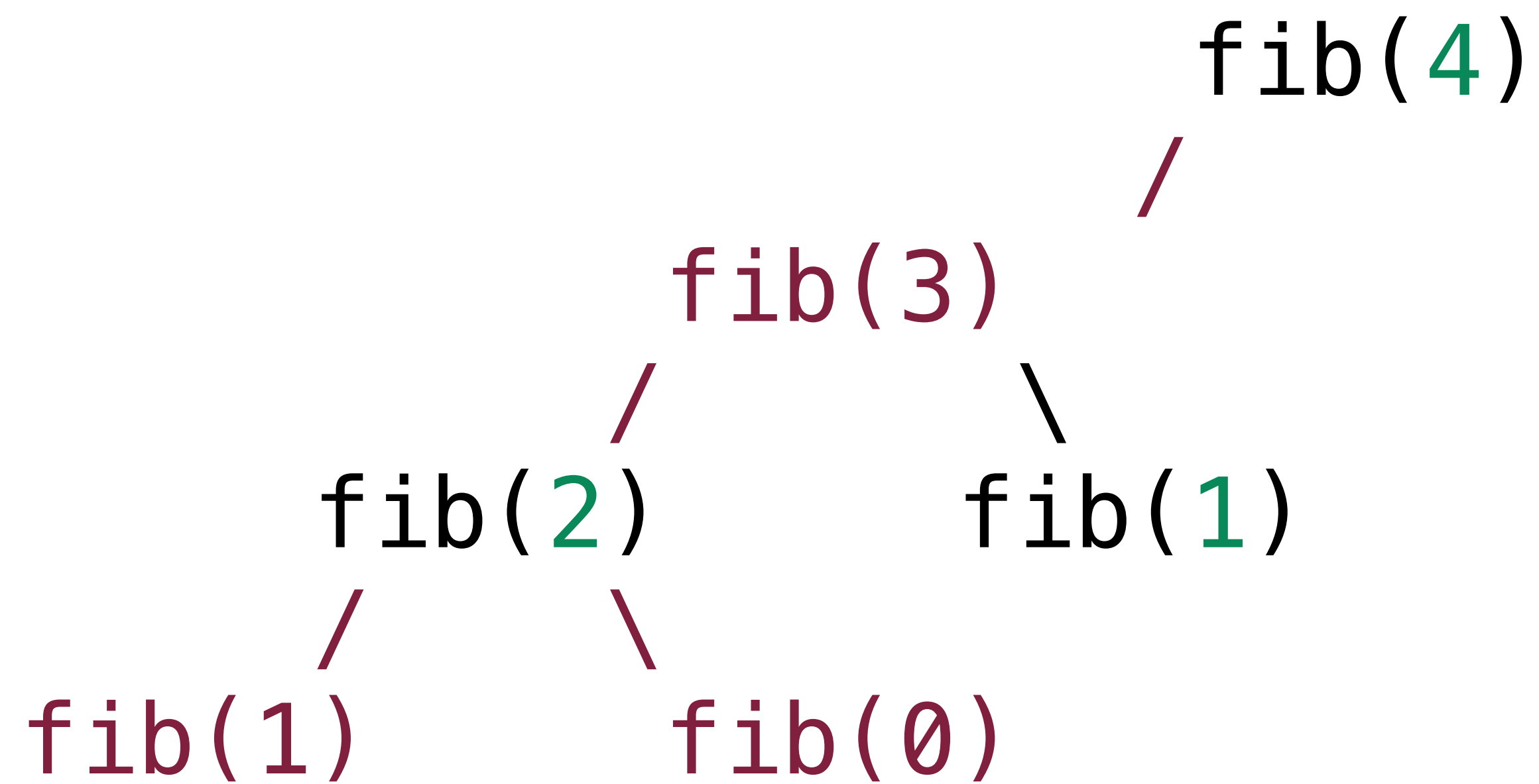
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  return memo[n];
}
```

```
memo = {
  2: 1,
}
```



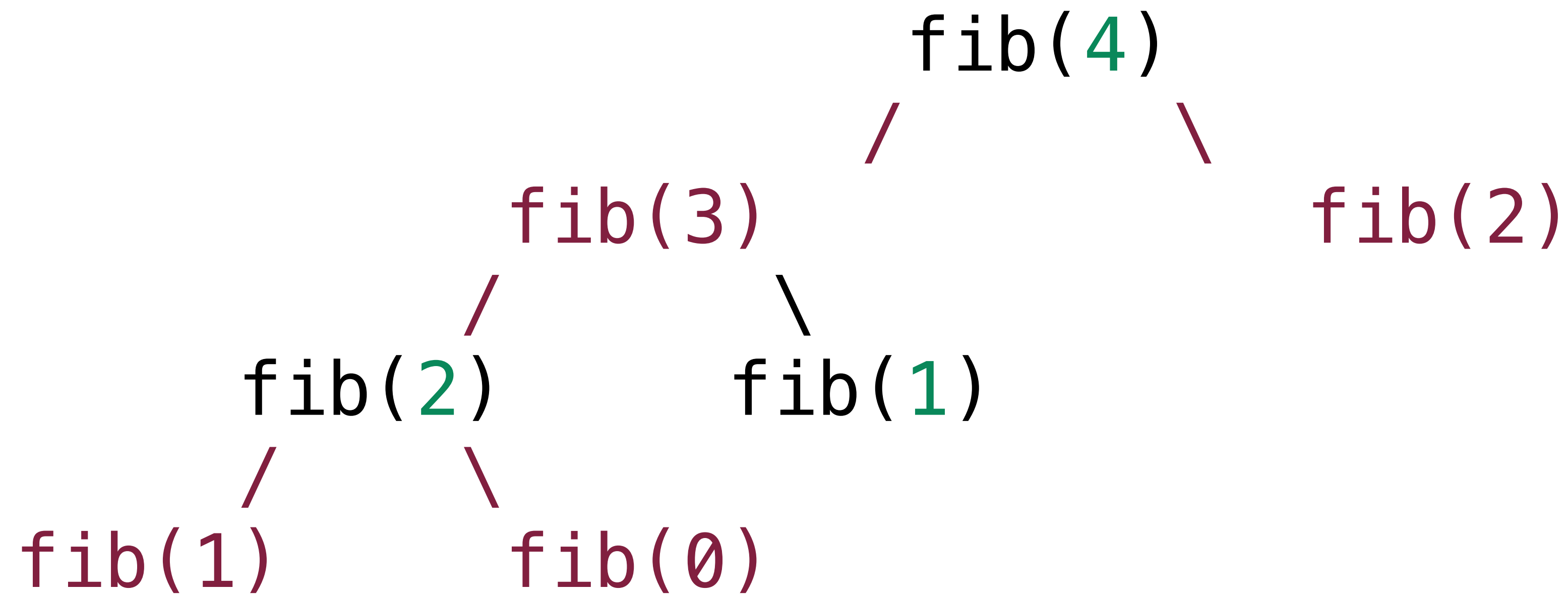
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  else if (memo[n]) return memo[n];
  else memo[n] = fib(n - 1, memo) + fib(n - 2, memo);
  return memo[n];
}
```

```
memo = {
  2: 1,
  3: 2
}
```



```
function fib (n, memo = {}) {
  if (n === 1 || n === 0) return n;
  else if (memo[n]) return memo[n];
  else memo[n] = fib(n - 1, memo) + fib(n - 2, memo);
  return memo[n];
}
```

```
memo = {
  0: 0,
  1: 1,
  2: 1,
  3: 2
}
```



# Space Complexity

- Big O can also express space complexity
- Measures how much space (i.e. memory) we use relative to the input (ex. by storing values in arrays and hash tables, and simultaneous calls on the call stack
  - Remember: what matters is the growth curve. not the actual number of bytes we store!
- Space can be taken and freed up again - the same can't be said of time!
- Usually, we have enough space...but not enough time!

```
// assume `callback` performs an  $O(1)$  operation
function map (arr, callback) {
  const newArr = []
  for (let i = 0; i < arr.length; i++) {
    newArr.push(callback(arr[i]))
  }
  return newArr
}
```

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```

# Multivariate Algorithms

- What if you have an algorithm that uses another algorithm?  
For example, what if you loop over an array of strings and sort each string?
- Be careful to not to confuse the input and runtime of the “outer” algorithm with the input and runtime of the “inner” algorithm

```
function sortedStrings (arr) {  
  for (let i = 0; i < arr.length; i++) {  
    arr[i].sort();  
  }  
}
```

// Let's say that .sort is  $O(n \log n)$



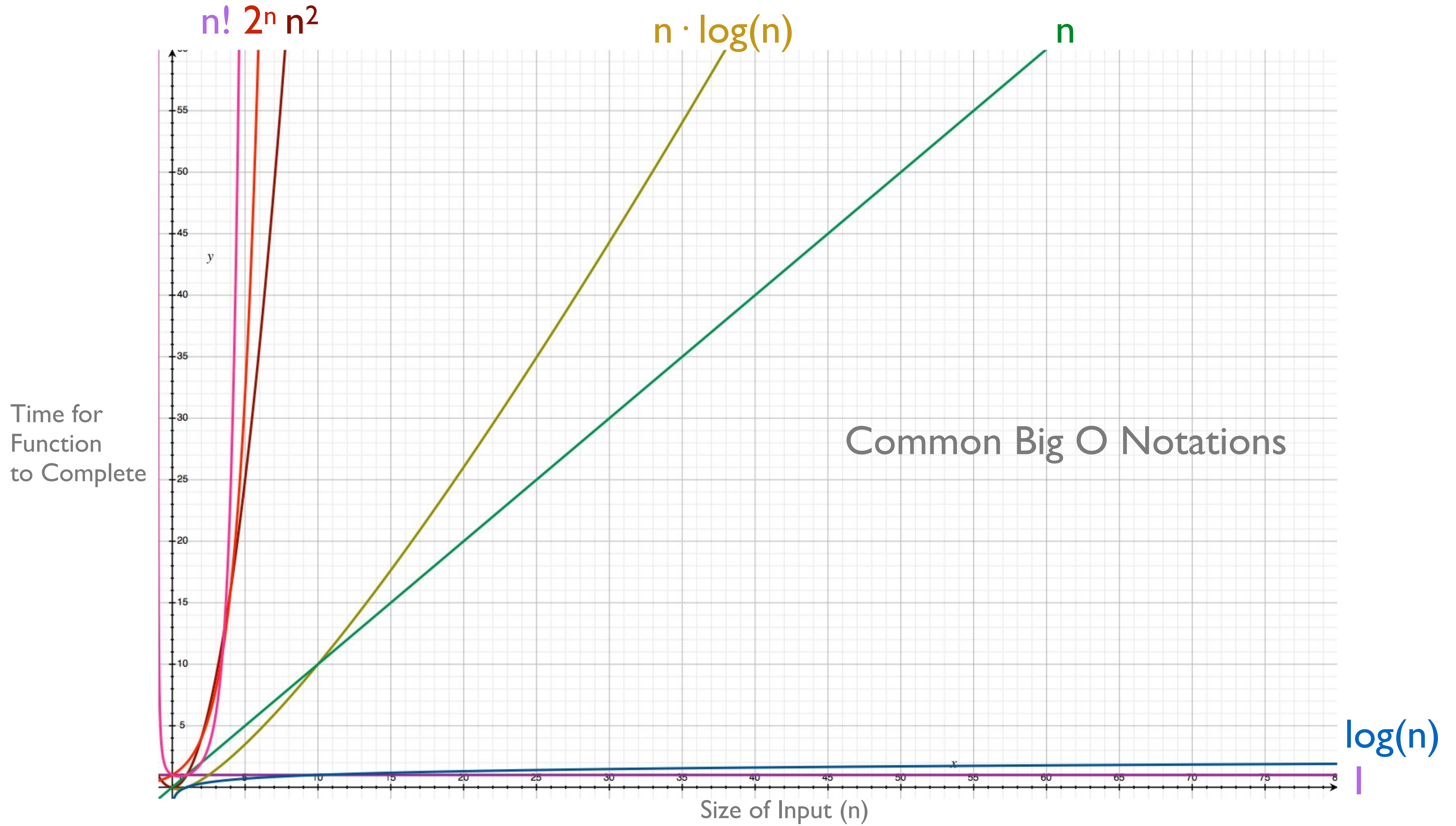
```
function sortedStrings (arr) {  
  for (let i = 0; i < arr.length; i++) { // 0(n)  
    arr[i].sort(); // 0(s log s)  
  }  
}
```

# Algorithm Analysis: Big O Notation

- A **comparative** way to classify different algorithms
- Based on **shape** of **growth curve** (*time vs input size(s)*)
- For **big enough** inputs
  - Might not be true when  $n$  is small, but who cares when  $n$  is small?
- Establishing an **upper bound** on the time
  - Not worse than this. Might be better, but it ain't worse!
- Including just the **highest order** term
  - In  $f(n) = n^3 + 5n + 3$ , only  $n^3$  matters as  $n$  gets large
- **Ignores constants** (mostly irrelevant;  $0.1 \cdot n^2$  will overtake  $10 \cdot n$ )

# A NICE MNEMONIC

- ◉ Different terms for different inputs
- ◉ Remove constants
- ◉ Axe the non-dominant terms
- ◉ Worst Case



# FUN EXAMPLE: REVISITING SUM UP

- We can actually optimize it to  $O(1)$
- Replit



# LEARNING OBJECTIVES

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  - Define what Big O is and why it's important
  - Calculate Big O for some simple algorithms
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  - Calculate Big O for recursive algorithms
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